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Accounting for Crises

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We provide one of the first empirical evidence consistent with recent macro global-game crisis models, which show that the precision of public signals can coordinate crises (e.g., Morris and Shin 2002, 2003; Angeletos and Werning 2006). In these models, self-fulfilling crises (independent of poor fundamentals) can occur only when publicly disclosed signals of fundamentals have high precision; poor fundamentals are the sole driver of crises only in low precision settings. We find evidence consistent with this proposition for 68 currency and systemic banking crises in 17 countries from 1983-2005. We exploit a key publicly-disclosed signal of fundamentals that drives financial markets, namely accounting data, and find that pre-crisis accounting signals of fundamentals are significantly lower only in low precision countries.

Economy-wide crises are often triggered when agents in an economy withdraw demand from markets for most goods and collectively rush to money or other "safe" securities. An important goal of economic theory is to understand when this collective and coordinated action is driven by fundamentals, and when by agents' self-fulfilling beliefs (e.g., Kindleberger 1978, Ch. 4). This goal is especially salient to current macroeconomic thought, which emphasizes the study

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of agents' behavior in financial markets (Bernanke 2010; Blanchard et al. 2010; Krugman 2010; Mankiw and Ball 2010, Section VI).[1] This emphasis on the financial sector is of course by no means new. In the Diamond and Dybvig (1983) model of the banking sector, self-fulfilling runs are always a possibility, while Gorton (1988), on the other hand, shows that fundamentals were the likely cause of panics during the U.S National Banking Era. More recent "global-games" models of coordinated action in financial markets allow for both fundamentals and self-fulfilling beliefs to cause crises (Atkeson 2000; Rey 2000; Morris and Shin 2002, 2003; Angeletos, Hellwig, and Pavan 2006; Angeletos and Werning 2006; Angeletos, Hellwig, and Pavan 2007). These models suggest that self-fulfilling crises are more likely to occur when public information that agents receive about asset fundamentals has high precision, and poor fundamentals are likely the sole determinant of crises when public signals about asset fundamentals have low precision. We find empirical evidence consistent with this hypothesis.

Global-games models envision a situation in which an asset has an unknown fundamental strength and falls if enough investors attack it. To decide whether to attack, each investor needs both knowledge about the asset's fundamental strength and a belief about what other investors are likely to do. We illustrate this mechanism by building a simple model extending Angeletos and Werning (2006, Section II). In our model, investors have initial heterogeneous private beliefs about an asset's strength (which facilitates subsequent trade) and receive an exogenous public (e.g., accounting) signal about its strength. The investors then trade, and the trading price (noisily) aggregates their heterogeneous beliefs as well as the public signal. Armed with the trading price, public signal, and her private belief, each individual trader then decides whether or not to attack.

[1] For example, Mankiw and Ball (2010) Figure 19.2 shows how a drop in financial asset prices can be self-fulfilling by reducing consumers' wealth and thus consumer spending and firm investment and, in turn, aggregate demand. In a similar refocus, Carvalho and Gabaix (2013) argue that the fundamental volatilities arising from firm and sectoral fluctuations are the primitives behind macroeconomic fluctuations in major world economies in the past half century.

As is standard in global games, our model's solution indicates that there is a threshold beyond which the problem becomes non-convex and admits multiple solutions. This threshold is more likely to be reached as the exogenous public signal's precision increases. The presence of such an exogenous signal is a new feature of our model compared to Angeletos and Werning (2006), where price is based just on the agents' private disagreement (and the supply shock). The introduction of an exogenous public signal alters several findings of Angeletos and Werning (2006). Specifically, the precision of the private disagreement no longer has a clear directional relation to the multiplicity threshold. This non-directional relation extends to the price's precision as well, because the price aggregates the private disagreement along with the exogenous public signal (and the supply shock). The clear directional movement towards the multiplicity threshold is thus special to the public signal's precision.

In an empirical setting, it is difficult to directly establish the presence or absence of multiplicity. However, one can exploit the economic intuition behind multiplicity, which is that precise public signals facilitate multiple self-fulfilling higher-order beliefs about other traders' attack decisions. Thus, pre-crises signals of fundamentals in the high precision regime take a wider range (i.e., pre-crisis signals could be either high or low), whereas pre-crisis signals in the low precision regime are typically low. This premise on the differing properties of pre-crisis signals across the two regimes is consistent with our model, and could be tested if one could locate a public signal that is an important input into price.

Samuelson (1970, Ch. 5 Appendix), Rajan and Zingales (1998, p. 569), and Summers (2000, p.10) nominate the accounting system as the source of such a public signal. In particular, if one considers the fundamental strength of the firm as its *economic* profits (an interpretation that is consistent with the definition of asset strength in Angeletos and Werning 2006, Section II), the accounting estimate of true profits is an obvious and important public signal. Note that economic profits are not the same as cash flows: for example, certain sales may have been made not in cash but on good credit. These sales transactions affect current economic profits, but are not reflected in current cash revenues. The accounting system therefore provides estimates of these transactions in the form of accounting accruals (Sloan 1996; Fama and French 2006). The "marking to economic value" process of accruals brings accounting profits closer to true economic profits, as evidenced by accounting profits' and accruals' superiority over cash flows in explaining stock returns as well as future cash flows (Dechow 1994; Barth, Cram, and Nelson. 2001). But the accrual estimation process naturally introduces measurement errors, driven both by uncertainty and managerial incentives. A deep body of accounting research has therefore developed empirical measures of the precision of the accrual estimation process. These precision measures can be usefully applied to test our model.

We next locate a market to test our hypothesis. The global-games models assume a market that is too large for any individual speculator and prone to collective actions such as the coordinated withdrawal of capital. We argue that currency crises and their "twin" banking crises constitute a powerful setting that meets these criteria. In an influential paper, Kaminsky and Reinhart (1999) find that the banking crises typically precede currency crises, and label them as "twin" crises. In line with our model, Kaminisky and Reinhart (1999, p. 473) note that either fundamentals or self-fulfilling expectations could be the cause for currency crises, which is the same argument made by Diamond and Dybvig (1983) in the context of banking crises. We therefore combine the two types of crises, and examine 68 currency and systemic banking crises in 17 countries from 1983 to 2005. We use the updated crises datasets of Kaminsky (2006) and the IMF (Laeven and Valencia 2008).

Our goal is not to create a forecasting model of crisis that can be applied to any country to assess the probability of a crisis in any given year; instead we are interested in assessing if crises that did occur were more likely preceded by poor signal realizations in the low precision regime than in the high precision regime. Towards this end, we follow the research design of Kaminsky and Reinhart (1999, Section III.A) and examine only countries with realized crises. Analogous to Kaminsky and Reinhart (1999, Section III.A), it is the presence of both tranquil and crises periods in our panel dataset that generates the requisite within-country variation in the accounting signals of interest.[2]

We construct a composite score of accounting precision for each country, based on the accounting data reported by its publicly-held firms. The accounting literature offers various empirical methods to estimate the precision of these accounting data, especially profits. We use six different precision measures from this literature, and construct a composite precision score for each country. We then use this composite score to split the countries into two groups of high and low precision.

To construct the realized accounting signals, we aggregate all the firms in each country to yield two annual, country-based measures of performance: accounting profits and accounting accruals (i.e., the accounting adjustments to cash flows to yield accounting profits). We recognize the rich empirical "early warnings" literature on currency and banking crises. The existing macro leading indicators used in this literature and its empirical specifications form the obvious baseline for our empirical tests.

We test the in-sample power of *past* accounting signals and other indicators to explain the occurrence of crises. Our unit of observation is the country-year for all variables. We represent the "twin crises" dynamics in a reduced form by constructing for each country year an indicator for recently suffered crises (within

[2] Our specification thus neither accounts for settings that were crisis-susceptible, but did not suffer one (due to luck or the central bank's preferences and actions or other factors), nor does it fully account for the true heterogeneity of the crises that did happen. Our tests thus may overstate our model's empirical validity. Kindleberger (1978, p.x) succinctly summarizes the perennial debate on the similarity and differences across crises by noting that some international economists are "clumpers" and others are "splitters".

the last 3 years). We also include, among other controls, country fixed effects to control for unobserved factors at the country-level.

We find that the pre-crisis accounting signals in low precision countries are significantly lower, as theoretically predicted. On the other hand, the pre-crises signals in the high precision countries are either insignificant or take higher values, an empirical finding consistent with the theoretical notion of multiplicity (which certainly allows for a pre-crisis boom). Figure 2 provides a comprehensive illustration of these results: both regimes show very similar behavior in tranquil years. But in the pre-crisis years, accruals and to a certain extent profits drop much more clearly in the low precision regime relative to the high precision regime. The drop in accruals indicates that the pre-crisis cash flows in low precision countries overstate economic profits. That is, the pre-crisis levels of cash flows may not be sustainable going forward, a sign of deteriorating asset fundamentals. This evidence is not only consistent with our model, but also demonstrates that the accounting system fulfills its stated purpose.

Section I formulates our hypothesis analytically and locates it in prior research. Section II describes our data and our empirical constructs. Section III presents the main results. Section IV concludes.

I. Model and Prior Research

This section models a coordination game, closely following and building upon Angeletos and Werning (2006, Sections I and II). We use their model and its notation as much as possible, for ease of exposition. Briefly, their Section I models a coordination game with an exogenous signal, while their Section II removes this public signal and instead models a public asset price based on private disagreement and a supply shock. We extend the model by including both an exogenous public signal (e.g., an accounting report) and a price based on this exogenous signal, disagreement, and a supply shock. This extension allows us to study the properties of the public signal in a financial market with a price.

There is a status quo and a unit measure of agents, each of whom has to decide whether or not to attack the status quo. Not attacking pays 0, while attacking pays $1-c, c \in (0,1)$ if the status quo is abandoned, and 0 – c if not. The status quo is abandoned if the measure of attackers is larger than the asset's fundamental strength θ. The critical range of θ where the outcome depends on the size of the attack is therefore $(0,1]$.

The initial belief on θ for all agents is an improper distribution. In the first step, each agent *i* forms her own private belief on θ. This belief could arise from any number of sources, and is represented by $x_i = \theta + \sigma_x \varepsilon_i, \varepsilon_i \sim N(0,1)$ being independent error terms across the agents. The dispersion in private beliefs is necessary to get trading started. Then all the agents receive a common exogenous public accounting signal $z = \theta + \sigma_z \varepsilon_z$. The error term ε_z follows a normal distribution $N(0,1)$ and is independent of all other error terms. In the third step, the agents, who have a CARA utility function with risk parameter γ, trade in the style of Grossman (1976), i.e., agents are price-takers with rational conjectures about the information content of price, and prices are determined by a Walrasian auctioneer. In the fourth and final step, based both on her private signal and the public signals *z* and price, each agent decides whether to attack.

We first compute the third step. The Grossman (1976, Equation 11) demand for a trader who observes both z and p is (we drop the index *i*):

$$k(x,z,p) = \frac{E[\theta \mid x,z,p] - p}{\gamma Var[\theta \mid x,z,p]}.$$

The aggregate demand over the unit continuum of traders matches the aggregate supply, which is the supply shock of $\sigma_e \varepsilon_e, \varepsilon_e \sim N(0,1)$ and independent of all other error terms.[3] The rational price function is conjectured as $p = \theta - \sigma_p \varepsilon_e$.

To solve the model, it helps to reframe the variances in terms of precisions $\alpha_x = \sigma_x^{-2}, \alpha_z = \sigma_z^{-2}, \alpha_p = \sigma_p^{-2}, \alpha_e = \sigma_e^{-2}$. Then we can write the conditional mean and variance as:

$$E[\theta \mid x, z, p] = \frac{\alpha_x x + \alpha_z z + \alpha_p p}{\alpha_x + \alpha_z + \alpha_p}$$

$$Var[\theta \mid x, z, p] = \frac{1}{\alpha_x + \alpha_z + \alpha_p}.$$

Equating aggregate demand and supply yields:[4]

$$\frac{(\alpha_x + \alpha_z)(\theta - p)}{\gamma} = \sigma_e \varepsilon_e$$

Solving for p yields $p = \theta - \frac{\gamma \sigma_e}{\alpha_x + \alpha_z} \varepsilon_e$ which in turn implies:

$$\sigma_p = \frac{\gamma \sigma_e}{\alpha_x + \alpha_z}, \alpha_p = \left(\frac{\alpha_x + \alpha_z}{\gamma} \right)^2 \alpha_e$$

The price thus aggregates both the private disagreement and the public signal, as reflected in σ_p.

We next turn our attention to the final fourth step, namely solving for the attack threshold. Each agent attacks if her signal x is less than the threshold

[3] The supply shock is necessary, as the price is otherwise fully revealing (Grossman 1976, Equation 32).

[4] Aggregating the i.i.d signals x_i over a unit continuum of agents requires integrating white noise, which is not Lebesgue-integrable, but can be distributionally integrated to a Brownian motion. We follow the implicit assumption of Angeletos and Werning and assume that the integral is instead θ, the mean of x_i. One potential way to justify for this assumption is to compute the per capita demand and supply for a countably dense subset of agents over the unit continuum. The law of large numbers applies to x_i in this case.

$\bar{x}(z,p)$, and the status quo is abandoned if $\theta \le \bar{\theta}(z,p)$, where $\bar{\theta}$ is the threshold level that is equal to the aggregate attack size $\Pr(x < \bar{x} \mid \theta)$. But $\Pr(x < \bar{x} \mid \theta) = \Phi(\sqrt{\alpha_x}(\bar{x} - \theta))$, where Φ is the standard normal CDF. We therefore get:

$$\bar{x} = \bar{\theta} + \frac{1}{\sqrt{\alpha_x}} \Phi^{-1}(\bar{\theta}).$$

Next, the expected payoff to an agent from attacking is $\Pr(\theta \le \bar{\theta} \mid x, z, p) - c$; therefore $\bar{x}$ must solve the indifference condition $\Pr(\theta \le \bar{\theta} \mid \bar{x}, z, p) - c = 0$. Note that each agent views $\theta \sim N(\frac{\alpha_x x + \alpha_z z + \alpha_p p}{\alpha_x + \alpha_z + \alpha_p}, \frac{1}{\alpha_x + \alpha_z + \alpha_p})$. This indifference condition therefore becomes:

$$\Phi[\sqrt{\alpha_x + \alpha_z + \alpha_p}(\bar{\theta} - \frac{\alpha_x}{\alpha_x + \alpha_z + \alpha_p}\bar{x} - \frac{\alpha_z}{\alpha_x + \alpha_z + \alpha_p} z - \frac{\alpha_p}{\alpha_x + \alpha_z + \alpha_p} p)] = c.$$

Combining the two equations above and substituting $\bar{x}$ leads to:

$$-\frac{\alpha_z + \alpha_p}{\sqrt{\alpha_x}}\bar{\theta} + \Phi^{-1}(\bar{\theta}) = \sqrt{1 + \frac{\alpha_z + \alpha_p}{\alpha_x}}\Phi^{-1}(1-c) - \frac{\alpha_z z + \alpha_p p}{\sqrt{\alpha_x}}.$$

Note that both $\bar{x}, \bar{\theta}$ are functions of z, p. We can reduce this dependence to one variable $z' = \frac{\alpha_z z + \alpha_p p}{\alpha_z + \alpha_p}$. The mean of z' is θ and the inverse of the variance $\alpha_{z'} = \alpha_z + \alpha_p$. The previous equation then becomes:

(1) $$-\frac{\alpha_{z'}}{\sqrt{\alpha_x}}\bar{\theta}(z')+\Phi^{-1}(\bar{\theta}(z'))=\sqrt{1+\frac{\alpha_{z'}}{\alpha_x}}\Phi^{-1}(1-c)-\frac{\alpha_{z'}z'}{\sqrt{\alpha_x}}$$

At this juncture, we can recast Proposition 1 of Angeletos and Werning (2006) as:

Proposition 1: *Uniqueness is guaranteed if* $\frac{\alpha_{z'}}{\sqrt{\alpha_x}}=\frac{\sigma_x}{\sigma_{z'}^2}\leq\sqrt{2\pi}$ *and multiplicity is possible only when* $\frac{\alpha_{z'}}{\sqrt{\alpha_x}}=\frac{\sigma_x}{\sigma_{z'}^2}>\sqrt{2\pi}$.

Proof: For every z', a candidate $\bar{\theta}$ always exists because the left hand side of (1) has a range of the entire real line. Differentiating the left hand side of (1) with respect to $\bar{\theta}$ yields $-\frac{\alpha_{z'}}{\sqrt{\alpha_x}}+\sqrt{2\pi}e^{\frac{1}{2}(\bar{\theta})^2}$, which is always positive if $-\frac{\alpha_{z'}}{\sqrt{\alpha_x}}+\sqrt{2\pi}\geq 0$. In that case, the left hand side of equation (1) intersects the right hand side at a unique $\bar{\theta}$.[5] See Figure 1 for an illustration.[6] •

[5] In addition, note that a low of value of *z'* leads to a high value of $\bar{\theta}$, making it more likely that the status quo will be abandoned.
[6] Multiplicities of intersection points are an inherent property of smooth surfaces (see Guillemin and Pollack 1974, Ch. 2.4 discussion of mod 2 intersection theory, for example). One can obtain uniqueness of the fixed point by imposing geometric restrictions on the problem (which global games achieve by lowering the precision of the public signal), but once these restrictions are relaxed or perturbed (e.g., by homotopy), multiplicities are inevitable. This is the key mathematical reason why the multiplicity property in global games is so robust. Figure 1 shows that the number of equilibria is almost always 1 or 3, and 3 is 1 mod 2. (Mod 2 intersection theory is typically developed for compact manifolds, but we can envision compactifying the curves in Figure 1 into closed curves on a finite torus as follows: consider the vertical strip $0\leq\bar{\theta}\leq 1$ and identify the line $\bar{\theta}=0$ with $\bar{\theta}=1$, then monotonically retract the resulting open cylinder to finite length, then take its closure, and then identify the end points of all the vertical lines on it. The curves are then homotopic to the generators of the torus, and therefore transversally intersect an odd number of times.) Finally, note that the realizations of z' that yield other than 1 or 3 intersections have measure zero due to Sard's theorem.

We can write $\frac{\sigma_x}{\sigma_{z'}^2} = \frac{\alpha_z + \left(\frac{\alpha_x + \alpha_z}{\gamma}\right)^2 \alpha_e}{\sqrt{\alpha_x}}$. We see that $\frac{\alpha_z + \left(\frac{\alpha_x + \alpha_z}{\gamma}\right)^2 \alpha_e}{\sqrt{\alpha_x}}$ is increasing in α_z and α_e, but the effect of α_x is ambiguous. If $\alpha_z \ll \alpha_x$, then it is increasing in α_x, but if $\alpha_z \gg \alpha_x$, then it is decreasing in α_x. This is in contrast to standard global games, where the multiplicity threshold is a function of $\frac{\sigma_x}{\sigma_z^2}$ and thus has a monotonic association with the private signal precision (Angeletos and Werning 2006, Section I). More important, note that that the precision of price $\left(\frac{\alpha_x + \alpha_z}{\gamma}\right)^2 \alpha_e$ contains α_x, so we cannot make any claims on the impact of the precision of price on multiplicity without knowing the *component* that caused the precision of the price precision to change. This is in contrast to Angeletos and Werning's (2006) Proposition 3, where all components of the precision of price affect the likelihood of multiplicity in the same direction.[7] Taking all these results together, one unambiguous claim we can make is that multiplicity is more likely as the precision of the public signal *z* increases.[8]

A. Testing the Model in the Context of Prior Research

We begin by cautioning the reader that the model's highly stylized nature demands significant concessions from its empirical tests. We cannot directly test the key comparative static that multiplicity is more likely where the public signal has high precision because we have no way to directly establish the presence of

[7] If the precision of the exogenous public signal *z* is zero, we indeed obtain Proposition 3 of Angeletos and Werning (2006). We have checked that all aspects of our model match Angeletos and Werning (2006) when the precision of *z* is zero.

[8] Note that multiplicity is obtained for certain as the precision of *z* tends to infinity, but uniqueness is not guaranteed as the precision of *z* tends to zero ($\sigma_e^2 \sigma_x^3$ could be $<$ or $> \frac{1}{\gamma^2 \sqrt{2\pi}}$).

multiplicity. However, the implication of multiplicity is that crises can occur in high precision settings for a wider range of the public signal realizations. To put it another way, crises in low precision countries are more likely to be preceded by low realizations of the public signal than crises in high precision countries. This is the proposition we test.

If the only public signal in the model were price, its precision would depend on private disagreement and the supply shock. Comparative statics on the supply shock are uninteresting (the shock exists primarily to create an equilibrium (Grossman 1976, Equation 32)); therefore Angeletos and Werning (2006) focus on private disagreement. While theoretically interesting, private disagreement, by its very definition, is difficult to directly test empirically.

This scenario changes with the introduction of the public signal z. Our empirical proxy for z is the accounting signal of economic profits. This accounting signal and its precision, in contrast to private disagreement, are measurable, and therefore allow us to test our main prediction (we build on this point further at the end of this section where we discuss other models).

We de-emphasize price as a signal because the precision of p does not have a clear empirical prediction. Furthermore, since our model is static, the price measures the same fundamental θ as the signal z. In reality, however, the accounting signal z measures current period economic profits, whereas the stock price is a dynamic summary measure of current and all future period profits. We would have to make significant adjustments to the stock price to bring it in accordance with our static model in a Grossman (1976)-type trading setting. We therefore relegate the stock price to a control variable, and show that the results are robust to its inclusion (see Section III).

The static nature of our model also implies that some adjustment for dynamics is necessary when testing the model using real-life data. Lacking theoretical guidance on dynamics, we employ a reduced form model by including a lagged dependent variable as a regressor. We assume that our time-series is deep enough to render the Hurwicz bias insignificant.

In a multiplicity setting, the number of intersection points is (almost always) an integer that jumps discretely when a critical geometric threshold is reached (e.g., Guillemin and Pollack 1974, Ch 2.4 and Figure 2). We therefore do not employ a continuous interaction term with the precision measure in our regressions, but instead nominate the cross-country sample median of the precision of z as a discrete multiplicity threshold that splits the sample into high and low precision countries.

An important caveat is that the multiplicity threshold depends not only on α_z, the precision of the public signal, but also on $\alpha_x, \alpha_e, \gamma$, i.e., the precision of the private disagreement, the precision of the supply shock, and the risk aversion. We cannot estimate these latter three parameters. So we have to assume that they take values that do not overturn our partitioning scheme. We have been unable to conceive of any direct tests of this assumption. The best we have been able to do is to use an alternative measure of accounting precision based on user perception (see Section III.D).

Finally, the model shows that, irrespective of precision, uniqueness obtains if the signals realizations are extreme (Figure 1).[9] We indirectly check this prediction in section III.D by examining the behavior of the signals prior to severe crises.

Our tests also accommodate prior studies on crisis predictions. A brief description of this literature is as follows. The first-generation analytical and empirical crisis research focused on monetary and exchange rate policies as the determinants of crises (Krugman 1979; Blanco and Garber 1986). Subsequent

[9] At extreme realizations of z', the left hand side of (1) is driven primarily by Φ^{-1}, which is a monotonic function. The results are also unique if $\theta \notin (0,1]$.

studies shifted to imperfections in financial intermediation as the cause.[10] This so-called 2nd generation crisis channel promptly raised issues of coordination and multiple equilibria based on self-fulfilling beliefs. Whereas initial studies of multiplicities focused specifically on banks, it became evident that multiplicities could also occur as a result of coordination and increasing returns issues in production (Blanchard 2000, Section IV.3). Other studies — the so-called 3rd generation crisis models — implicated very specific financing channels, such as debt denominated in foreign currencies. More recent arguments have further broadened the scope of financial markets: Blanchard et al. (2010) note that "little attention was paid, however, to the rest of the financial system [apart from banks] from a macro standpoint," and Krugman (2010) notes that crises need not necessarily arise from specific financial markets, such as the international exchange rate markets or corporate debt financed in foreign currency (i.e., the balance sheet effect); a collapse in the prices of any asset market that prevents firms from securing financing for ongoing operations is sufficient to trigger a crisis.

Because the primary role of financial markets is to finance the production sector, an immediate consequence of broadening the financial markets in a crisis context is that the country's production sector comes to the forefront. Modern models of crisis, in contrast to their first-generation counterparts, emphasize the production sector and the economy at large (Tornell and Westermann 2005; Martin and Rey 2006; Ranciere, Tornell, and Westermann 2008), suggesting important roles for financial markets and sources of financial information on firm performance. To the best of our knowledge, there has been no attempt in the early warnings literature to use accounting information to predict currency crises.[11]

[10] Early 20th century accounts of crises had implicated financial intermediation as a key cause of crises (Blanchard 2000, Section IV.2; Samuelson 2009), but the focus shifted away with the emergence of the IS-LM model and its descendants.
[11] Swanson, Rees, and Juarez -Valdes (2003) study the information content of accounting figures *following* the 1994 Mexican currency devaluation.

Finally, on the subject of coordination issues, Jeanne (1997) and Jeanne and Masson (2000) use non-linear empirical tests such as Markov switching to identify self-fulfilling beliefs in the devaluation of the French franc. Multiplicity in these models arises from factors such as central bank preferences that are not directly observable (see Jeanne (1997), Proposition 1). Consequently, these studies must infer the underlying parameters from data patterns, and then conclude based on the parameter estimates whether the crisis was self-fulfilling or not. While these unobservable factors could clearly be operational in our sample (and our model has several such parameters as well), our empirical prediction on where fundamentals work and where they do not is based not on unobservable parameters that must be inferred from the data, but on observable parameters such as the precision of the accounting signals. It is this observable feature of some of our underlying parameters that grants our empirical tests the power to reject the model.

II. Data and Variable Definitions

A. Currency Crises and Financial Data

As mentioned earlier, our goal is not to create a forecasting model that predicts the probability of crisis in any country in any year; instead our goal is to examine the association between fundamentals and actual crises. We therefore follow the research design of Kaminsky and Reinhart (1999, Section III.A) and Gorton (1988) and others, who attempt to uncover the role of fundamentals in panics by analyzing the behavior of signals of fundamental during panic periods relative to some control tranquil periods. We likewise limit ourselves to countries that have experienced crises. Our sample choice ignores settings that did not experience crises, but would have been classified as crisis-susceptible by our model. This omission likely overstates the fit of our model.

To identify crises, we closely follow prior studies. Given the twin nature of banking and currency crises (Kaminsky and Reinhart (1999)), we use both types of crises. Kaminisky (2006) updates the data of Kaminsky and Reinhart (1999) and provides a detailed catalog of banking and currency crises. As explained in Sections 4.1 and 4.2 of her study, Kaminsky (2006) uses 18 indicators to identify crises, and uses a regression tree methodology to classify the type of each crisis. Her online appendix provides the classifications and the dates of each crisis episode.[12] In addition to Kaminsky (2006), the IMF has also produced its database of currency and systemic banking crises. This is publicly available as Laeven and Valencia (2008), which is an update of Caprio et al. (2005). We use both the Kaminsky and IMF data sets. Our Table 1 provides the details the country-years of our crisis sample.[13]

In a few cases, the two datasets do not coincide, in which case we use Kaminsky (2006). Another interesting observation is that some ERM currency episodes such as the devaluation of the pound in 1992 do not make it into both datasets.[14] We do not second-guess these choices. Also note that because our accounting data are annual, we only record the year of the crises. We next turn to accounting data.

We collect firm-level accounting data from Thomson Datastream, which contains accounting information from the annual reports for each fiscal year of publicly traded companies around the world. To be included in our sample, a country must have more than five firm-year observations with non-missing values for a number of accounting variables, such as total assets, current assets, current

[12] http://home.gwu.edu/~graciela/HOME-PAGE/RESEARCH-WORK/MAIN-PAGE/working-papers.htm

[13] To justify their sample of crises, Kaminsky and Reinhart (1999, p. 474) quote Kindelberger (1978, p.14): "For historians each event is unique. Economics, however, maintains that forces in society and nature behave in repetitive ways. History is particular; economics is general." Our sample selection choice therefore also faces the same critique. For an institutional analysis of crises, see Krugman et al. (1999).

[14] See Kaminsky (2006, footnote 29) for a discussion of her classification of the ERM crises. Her comments resonate with Krugman's (1999, p. 438) observation that European countries that abandoned their principles seem to have gone completely unpunished. Also see Buite, Corsetti, and Pesenti (1998) for a theoretical and institutional discussion of the ERM crises.

liability, and net operating income. Datastream defines each firm observation by the unit of equity it issues. Thus, if a firm issues equities on two different exchanges, it will count as two firm observations. Because securities listed on a foreign exchange can also be subject to the accounting rules of the foreign country, we delete securities cross-listed on the U.S. stock exchanges. This deletion ensures that the accounting signals of each country are mostly an outcome of the local accounting standards.

Our procedure yields 75,956 firm-year observations from 17 countries that experienced crises. The limited availability of firm-year observations in earlier years restricts our analysis to crisis episodes after 1983. This truncation removes some early reserves-based crises and makes the sample more relevant to our financial market based hypothesis. We then aggregate the firm-years into country-years (we do not over-weigh country-years that have more firm-year observations). Our sample ends in 2005. These country-years include 68 crises.

Table 1 shows our country sample, along with the classifications based on Kaminsky (2006, Table 4). Many of the crises events can be classified as either financial excess or sovereign debt. These types of crises typically arise from financial illiquidity problems following a period of high expansionary credit growth (Tornell and Westermann 2005). Financial markets thus appear to be important drivers of these crises, making them an appropriate setting for our study.

We use the country-year panel dataset of 17 countries in the years 1983-2005 for all our analyses. The presence of both tranquil and crises periods in our panel dataset generates the requisite (within-country) variation in the accounting signals of interest, analogous to Kaminsky and Reinhart (1999, Section III.A). Our decision to use all the above crises in the same panel dataset clearly obscures much heterogeneity, a crucial one being the cross-sectional and time-series differences in factors such as central banks' willingness to defend the exchange rate. The tranquil years in a country may also not be comparable because some years could contain failed attacks and other shocks.[15] Finally, Buite, Corsetti, and Pesenti (1998) develop a multi-person game of crisis and argue that the appropriate unit of observation may not be a country, but a *cluster* of countries. We make no attempt to identify such country clusters. Our unit observation is an individual country-year.

Table A1 (in the online Appendix) reports the crisis years as well as the number of public firms in our sample for each of the country-years. There is considerable variation in the number of firm-year observations across countries, reflecting differences in the level of industrialization, financial market development, and data availability. The shaded areas in Table A1 show considerable variation in the spread of crises across countries and time. Crises have some tendency to be clustered, reflecting the existence of the well-known "contagion effect" (Allen and Gale 2000; Kaminsky, Reinhart, and Vegh 2003; Yuan 2005).

B. Precision of Accounting Signals

We now describe our composite measure of accounting precision for each country. The accounting literature — see summaries in Dechow and Skinner (2000) and Healy and Wahlen (1999) — has extensively researched the precision or ability of accounting measures to capture true economic profits. The source of accounting (im)precision arises from the following problem: period *t* cash flows are not period *t* economic earnings. For example, some sales could have been in the form of credit or accounts receivables, and thus do not appear in cash revenues. Alternatively, some assets may have to be written off, leading to an economic loss, but there may be no immediate cash flow impact. Accounting

[15] However, Figure 2 shows that, at least for the accounting signals, the tranquil periods appear tranquil; see Section III for details.

therefore adjusts cash flows to construct a measure of earnings or profits. This adjustment, called accruals, brings the accounting earnings figure closer to economic profit (Dechow 1994; Barth, Cram, and Nelson. 2001).

To users of financial statements, these accrual adjustments are *relevant*, but their *reliability* can be imperfect. Specifically, the reliability, or precision, can be impaired because management can misuse its discretion over accruals to conceal economic reality, or it can make estimation errors. The noise in these adjustments is our proxy for the precision of the public signal. Note again that we are not measuring the variance of the overall performance signal; we are measuring the noise in the accounting *adjustments*. This is precisely the measure that the crisis models require.

But what factors contribute to the quality of the accounting estimates? In addition to proximate factors such as audit quality and capital market discipline, recent accounting research points to deeper institutional factors such as accounting rules, legal enforcement, and the legal regime (e.g., Ball, Kothari, and Robin 2000). These factors vary across countries, yielding the institutionally-driven cross-country variation in our sample's accounting precision (we discuss this point more at the end of this subsection).

While recognizing accounting precision's conceptual and institutional importance, the accounting literature has not converged on a universally accepted measure of accounting precision. Different accounting studies pick different properties of accruals to measure the precision of accounting profits. We employ six commonly used measures that capture various dimensions along which accounting information reliably reflects the relevant firm fundamentals. Table 2 defines these six measures in detail, as well as their sources in the literature. We aggregate each measure to the country level by using the median of the firm-year observations. We sign the measures so that lower values reflect higher precision.

Our first measure of accounting precision, accruals quality (=AQ^1), captures the estimation errors in the accounting process by measuring how well accrual estimates map into cash flow realizations. Following Dechow and Dichev (2002), we operationalize this measure as the standard deviation of the residual from a country-level regression of current accruals on multi-period operating cash flow. A lower standard deviation implies higher accounting precision.

Our second measure, AQ^2, proxies for the level of management discretion, often known as "smoothing" behavior (Fudenberg and Tirole 1995; Trueman and Titman 1988). Smoothing refers to managers misusing their reporting discretion to conceal economic shocks by over-reporting poor performance and under-reporting strong performance. The accounting literature has traditionally used a strong negative correlation between changes in accruals and operating cash flows to proxy for management intervention over and above the natural level of accruals accounting (e.g., Francis et al. 2005). The negative of this correlation is then our AQ^2 measure.

The remaining four measures of accounting precision (=AQ^3, AQ^4, AQ^5, and AQ^6) are various measures of the magnitude of accruals. Sloan (1996) suggests that large accruals involve a higher degree of subjectivity that can often result in both intentional and unintentional reporting errors. Leuz, Nanda, and Wysocki (2003), on the other hand, argue that the larger the absolute magnitude of accruals, the more room the manager has to exercise discretion in reporting earnings. We measure these two concepts both with current accruals (=AQ^3, AQ^4) that arise from operating activities, and total accruals (=AQ^5, AQ^6) that include accruals from both operating and financing activities. We scale the accruals as per the original papers.

Then, as defined in Table 2, we construct a composite measure of accounting precision from the six AQ measures to eliminate potential measurement error. We rank each measure across all countries and take the mean of the six ranks as a composite country index of accounting precision. This is our country-based measure of the precision of the public signal.

Table 3 sorts the countries in ascending order based on the composite index, with lower scores reflecting higher accounting precision. All six individual measures exhibit large variation across countries, but similar rankings in terms of relative magnitudes. The magnitudes of the measures conform to prior literature (Bhattacharya, Daouk, and, Welker 2003, Table I and III; Leuz, Nanda, and Wysocki 2003, Table II), with some differences due to different sample periods. Finally, we dichotomize the sample at the median into countries with high and low accounting information precision. Table 3 provides the results.

With some exceptions, emerging markets are likely to be low precision countries, and mature markets the high precision countries. Our precision classification is also in line with prior studies that suggest that institutional characteristics (La Porta et al. 1997) and the enforcement of contracts (Ball, Kothari, and, Robin 2000) are related to the accounting information environment. For example, Table 3 shows high ranks for European countries, such as Denmark, Finland, Spain, and Sweden, whereas developing countries like Argentina and Brazil rank among the countries with low accounting precision. We examine the enforcement issue systematically using the rule of law index from the *International Country Risk Guide*, which ranks countries on a rule of law index (0-10), 10 being the highest. The average score for our high precision countries is 8.29, which is significantly higher ($p = 0.012$) than the average score of 5.65 for the low precision countries. Our accounting precision dichotomy thus appears to have some degree of institutional validation.

C. Realized Accounting Signals

Having described the precision of the public accounting signal (signal z), we now turn to the measurement of the signal itself. Table 4 provides the definitions for the two accounting signals we use to operationalize the realization of the signal z. The two measures are a) accruals and b) accounting earnings (or profits). These measures are particularly well suited to global games' notion of fundamental strength (or θ) because highly profitable entities likely have lower demand for interim external financing (Kaplan and Zingales 1997). Note that our measures pertain to actual firm operations because our primary object of interest is operating asset strength, not investors' propensity to continue financing.[16] We obtain the median of each measure *separately* for each country-year and nominate it as the countrywide measure for that year.

Realized Accounting Signal: Operating Profitability.— The first accounting signal that we employ**,** operating profitability, requires little motivation. Dechow (1994) shows that investors perceive operating earnings to be a more important performance measure than operating cash flows. We define operating profitability as the country median of firm-level net operating income scaled by beginning total assets. Table 4, Panel B indicates that operating profits average a reasonable 8.5 percent of assets.

Realized Accounting Signal: Operating Accruals.— The second accounting signal we employ, $Accruals_{c,t}$, represents the adjustment to cash flows to yield accounting earnings, all based on operating activities, to more accurately reflect the economic strength θ.

[16] The terminal asset value in global-games models depends both on the current operating fundamentals and the likelihood that investors will provide the requisite refinancing. For a study that empirically distinguishes the first factor from the second in a manner similar to ours, see Andrade and Kaplan (1998).

Our focus on operating accruals has substantive precedence in the valuation literature (e.g., Jones 1991; Dechow, Sloan, and Sweeney 1995; Sloan 1996; Fama and French 2006). In addition to changes in current operating assets and liabilities, our definition of operating accruals includes the reversal of certain non-current operating asset accruals by subtracting depreciation and amortization. We compute accruals from the balance sheet and income statement information. We do not use the cash flow statement to compute accruals because of the limited availability of cash flow information across countries and time.

Note that accrual quality forms the basis of our measure of the precision of accounting information. However, the aggregation process we use to arrive at the precision measure is very different from the realized accrual signal itself. The cross-country variation in the levels, magnitudes, and other higher moments of accruals serves as a proxy for accounting precision, while the within-country variation serves as a signal of fundamentals.[17] Table 4, Panel C shows that the two accounting signals, profits and accruals, are correlated at 0.63 in our sample.

D. Macroeconomic Leading Indicators in Prior Literature

The general conclusion of the crisis prediction literature is that an effective warning system should consider a large variety of indicators (Edison 2003; Kaminsky, Lizondo, and Reinhart 1998). We adopt the leading indicators proposed in Appendix A of Edison (2003), who constructs this list by building upon Kaminsky, Lizondo, and Reinhart (1998). Following Edison (2003), Table 1), we group our list of 18 indicators into five major categories: current account indicators, capital account indicators, real sector indicators, domestic financial indicators, and global indicators.

[17] This is akin to the standard statistical estimation of mean and standard deviation, where the same underlying data are aggregated differently.

Table A2, Panel A provides definitions for all 18 leading indicators, their data sources (primarily the International Financial Statistics), and the predicted direction of changes prior to a currency crisis. All indicators are defined as a percentage change from the previous year, except for the indicators that already measure deviation from a trend.[18]

III. Results

This section proceeds in four stages: we first show the univariate results graphically. We then show the results in a multivariate setting. We then analyze the multivariate results by providing detailed economic explanations for the coefficients of the accounting signals. Finally, we conduct robustness tests to examine the sensitivity of our results.

A. The Story in Pictures

Figure 2 reports the movement in the accounting signals three years before and after the crises. Accounting signals show clear movement around the crises, with pre-crisis accruals dropping more clearly for low precision countries, indicating, in a sign of deterioration of fundamentals, that the pre-crisis levels cash flows may not be sustainable going forward. This result for low precision countries is consistent with our prediction. The trends are more similar in profits. By contrast, in the tranquil years the data are indeed tranquil across both sets of countries (and similar in magnitude). This feature gives us confidence in the validity of both our crises and tranquil periods, and in our decision to use these periods to generate within-country variation in our accounting signals.

[18] Those two indicators are the excess real exchange rate and excess real M1 balances. Also, if a macroeconomic series is missing entirely for a given country, we assume that that series is zero in order to retain that country in our regression analysis. The presence of country fixed effects in all our regressions should mitigate the impact of this data choice on the other countries in the sample. Section III.D provides robustness tests related to the indicators.

The reader may wonder about the negative accruals in the tranquil periods. Table 4, Panel B indicates that the mean of accruals is -0.006. For comparison, Sloan (1996, Table I) reports accruals of -0.03 for US firms. More interestingly, recent studies such as Hirshleifer, Hou, and Teoh (2009) find that, at the aggregate level, accruals are positively associated with growth and future performance. The downward trend in accruals before a crisis in low precision countries is therefore not unexpected. Section III.C provides more insight into the specific nature of the movements we see in Figure 2.

B. Multivariate Analysis

We next conduct an in-sample analysis with our country-year panel data set using multivariate regressions. We specify the following probit model, which we run separately for high- and low-precision subsets of countries (i.e., $X = H, L$ below). This specification allows for the coefficients for all regressors to vary across the two subsets:

$$(2)\ \ \mathrm{D\_crisis}_{c,t} = \alpha_X + \sum_{i=1}^{2} \beta_X^i \times \mathrm{Acc.Sig.}_{c,t-n}^{i} + \lambda_X \times \mathrm{LDV} + \sum_{k=1}^{18} \gamma_X^k \times \mathrm{Lead.Indic.}_{c,t-n}^{k} + \varepsilon_{c,t}$$

The dependent variable is an indicator variable that turns on when country *c* has a crisis in year *t*. LDV is the lagged dependent indicator variable that takes a value 1 if there was a crisis in the same country in the last three years. Our specification is thus a reduced-form dynamic model.

The coefficients β_H^i (β_L^i) measure the associations between the crisis year *t* and years $t-n, (n = 0,1,2)$ accounting signals for subsets of countries with high (low) accounting precision (all accounting signals in the two pre-sample years 1981 and 1982 are coded as missing). In addition to the accounting signals, we also use the 18 leading indicators described in Section II.D. Our choice of windows of up to two years prior is based on Kaminsky and Reinhart (1999, Section III.A), who argue that early warning signals occur in a 24-month prior period for currency crises and a 12-month prior period for banking crises.

The majority of the early warnings literature takes the signals approach (Kaminsky and Reinhart 1999, Section III.A), where the indicators issue a signal whenever they move beyond a certain threshold (this threshold is calculated from the data itself). However, our ability to estimate the optimal threshold is impaired by the limited frequency of annual accounting data. Our use of multivariate probit models thus mirrors Frankel and Rose (1996), who use similar predictive and contemporary regression specifications in their Table 1.[19]

We also include country fixed effects to control for any unknown country-level factors that are constant over time but that vary by countries (the intercept in equation (2) must therefore be viewed as a short-hand for the fixed effects). The fixed effects thus shift the baseline probability of a crisis but do not absorb the effect of time-varying crisis predictors on crises (Bertrand, Duflo, and Mullainathan 2004, equation 1). We also allow for a time trend and within-year cross-sectional correlations in the error terms (to account for contagion-type effects).

Before we discuss the results, we wish to emphasize that the word "predict" in the ensuing discussions should be construed as a shorter way of writing "explanatory power" of prior-year accounting signals. We do not mean for "predict" to have a forecasting connotation, because our sample only contains countries that had crises, not the world at large.[20]

We first present the results *without* the precision dichotomy. Recall we have no conjectures for the accounting signals over the entire sample. The results, in

[19] Berg and Pattillo (1999) assess the pros and cons of the two approaches, and conclude in their Section 3.2 that probits slightly outperform the signal threshold approach.
[20] Gorton (1988), Kaminsky, Lizondo, and Reinhart (1998), Berg and Pattillo (1999), Kaminsky and Reinhart (1999), and Edison (2003), among others, conduct similar in-sample exercises.

Table 5, show that accounting signals overall have no predictive power. Some of the significant one-year ahead early warning indicators are: real exchange rates, industry production, excess real M1 balances, domestic credit, commercial bank deposits, and oil prices, all with the predicted signs. There is certainly much variation in prior studies' findings on the early warning indicators, but we believe that our findings square well with the last but one column of Edison (2003, Table 5), which shows that these signals have some of the highest probability of predicting a crises when they are emitted. Likewise, Frankel and Rose (1996, p.351) also show that a drop in industry production and a high growth in domestic credit, among other factors, are significant predictors in crashes. These results give us some comfort on the empirical validity of our setting.[21] Finally, the lagged dependent variable is not significant in the one-year ahead predictive model, but is in the two-year ahead predictive model. Thus, although crises are not highly autocorrelated events, it is important to control for their dynamics.

C. Main Results

We now compare the predictive power of the accounting signals across the two groups of accounting precision. Table 6 presents the results. Recall that accruals are adjustments made to the cash flows to compute economic or accounting profits. Holding accounting profits constant, a decrease in accruals implies that a smaller portion of the current economic profit will be realized as future cash flows. In other words, future cash flows are likely to be lower than suggested by current cash flows. A classic example of a negative accrual is a write off. Write-offs immediately recognize the loss of future benefits of some asset. However, this information cannot be gleaned from this period's cash flows. Another negative accrual is an increase in account payables (e.g., delaying

[21] Please see Table A3, Panel A for the average marginal effects of the probit coefficients.

payments to employees and vendors). This accrual recognizes an increase in future cash obligations, an event that has no immediate impact on current cash flows. Thus, decreases in accruals reflect the manager's recognition of increases in future obligations (or decreases in future benefits) that are yet to happen, and therefore not evident in current cash flows. A similar argument in the opposite direction can be made for positive accruals (such as an increase in current receivables that will turn into cash later).[22]

The economic time-series interpretation of accruals above is consistent with the statistical within-firm variation interpretation of the coefficients in the panel regressions in Table 6 with fixed effects. Table 6, Panel A shows that two years prior to the crisis in high precision countries, the accrual coefficient of 20.245 is positive and statistically significant: managers are actually expecting a higher portion of the current economic profits to be realized in the future (i.e., future cash flows are likely to higher than suggested by just the current cash flows). This is consistent with our model which, because of multiplicity considerations, makes no directional predictions on the link between fundamentals and crises for high precision countries: in these countries, the model indicates that self-fulfilling beliefs are more active and crises can hit for a wider range of fundamentals.[23]

In the year prior to the crisis, accounting signals in high precision countries show no impact, a finding also consistent with the presence of multiplicity in this region. But in the low precision countries, accruals decline significantly at the 5 percent level. This is what our model predicts when it states that low signal realizations are the unique cause of crises in low precision settings.

The coefficients of the probit regression cannot be interpreted directly. In Table A3, Panel B, we compute the marginal effect averaged over all the

[22] It is for these reasons that Barth, Cram, and Nelson (2001) find accounting earnings and accruals to be superior predictors of future cash flows than current cash flows themselves.
[23] These results are also consistent with Frankel and Rose (1996), Kaminsky and Reinhart (1999), and Rancier, Tornell, and Westermann (2008) who document a domestic boom prior to crises.

observations. In the pre-crisis year for the low precision countries, the coefficient on accruals is -0.346, suggesting that for a .01 decrease in accruals, the probability of a crisis in these countries in the subsequent year increases by 0.346 percent. This is about the same magnitude that Frankel and Rose (1996, p. 362) report for their FDI inflows regressor. A 0.01 decrease in accruals is quite feasible is our sample; Table 4, Panel B indicates that the standard deviation of accruals is 0.268. These magnitudes provide economic plausibility to the important result that pre-crisis accruals are significantly lower only in the low precision countries.[24]

The results on accruals thus far obtain after controlling for profitability. As an additional check, Table 6, Panel B shows that the same results on pre-crisis accruals obtain even after dropping the profitability regressor (the average marginal effects in Table A3, Panel C are also similar). The robustness of the accruals result is particularly valuable because it shows that accounting practices matter: it is the application of accounting rules to the measurement of firm operations that generates critical asset-pricing information. Accounting adjustments thus play the role they are supposed to play (Summers 2000, p.10).[25]

To investigate our pre-crisis accruals results further, we test if any systematic component of accruals is causing the results. We decompose accruals into

[24] Table A3 also reports the standard error of the marginal effects, which are computed using the delta method that linearizes the average marginal effect using the first order Taylor expansion. The significance of other coefficients in Table A3, Panel B largely line up with Table 6, Panel A. One difference is that the profits in low precision countries in the pre-crisis year are positively significant. Holding accruals constant, an increase in profits suggests an increase in cash flows. One explanation for the positive coefficient on the pre-crisis profits and negative coefficient on the pre-crisis accruals in the low precision countries is that the pre-crisis cash flows are booming, but managers are indicating via accruals that these cash flows are not going to persist in the future.

[25] Although the accounting data are impacted by a country's institutions, the accounting signals could gain power in low precision countries because of more severe institutional measurement weaknesses in other early warning signals. Likewise, accounting signals could lose significance in high precision countries because of the institutional measurement superiority of other early warning signals. The predictive significance of the accounting signals in both high and low precision countries (albeit at different times) should partly alleviate this concern. Table 6 also indicates that the explanatory power of the other leading indicators (excluding the accounting signals) in the pre-crisis years are not that different across the two sets of countries (the year -1 yields an explanatory power of 0.348 for low precision counties and 0.376 for high precision countries). One explicit way to check for the unreliability of macroeconomic series is suggested by Michalski and Stoltz (2013), who use deviations from Benford's laws to infer strategic misreporting of macroeconomic data. However, those authors note on p.598 that their statistical approach is better suited for quarterly data, and not for annual data (that we use). We therefore acknowledge the possibility of systematic quality problems in our macroeconomic series, but make no corrections to them.

changes in current operating asset (ΔCA), changes in current operating liability (ΔCL), and depreciation. At this detailed level of granularity, different firms could be adjusting different factors of account; so one may not expect any one component of accruals to be the systematic predictor of crises, even when total accruals are. And in fact, we are unable to see any meaningful systematic variation in any particular subset of accruals.[26]

The crisis year is equally interesting. First, all McFadden R^2 are much higher, suggesting that all measures are better at reflecting the occurrence of a crisis than predicting it. The high precision countries consistently show a significant decline in profits and accruals at the end of the crisis year, suggesting that although the causes of the crises were not associated with low signal realizations, the occurrence of crisis is followed by low signal realizations. This aftermath is consistent with the message of Reinhart and Rogoff (2009). However, the same cannot be said of the low precision countries. Although the signals were low in these countries pre-crisis, they show no significant deterioration in the aftermath. The profit effect is neutral and accruals actually pick up significantly after the crisis, suggesting more confidence in the future.

One potential explanation for the above result comes from the cross-sectional variation in the aftermath of crises, as shown in Figures 1-4 of Reinhart and Rogoff (2009). Those figures indicate that many of our low-precision countries show a shorter duration of the aftermath than many of the high-precision countries.[27] Reinhart and Rogoff (2009, p.469) themselves make the observation that emerging markets do better than advanced countries in employment recovery, speculating as causes structural macroeconomic factors such as a greater downward flexibility in wages in emerging countries. Such positive economic

[26] A similar point is made in a different context by Bertrand, Mehta, and Mullainathan (2002), who argue that because activities such as expropriation can take many forms, their systematic evidence should be present in overall measures of firm performance measures rather than their specific components.
[27] For example, in their Figure 3, the duration of unemployment was about 3 years for the 1997 Malaysian crisis, and about 7 years for the 1987 Norwegian crisis.

factors could, in the aftermath, increase the coefficient on accruals in the low precision countries. Additionally, the same structural macroeconomic flexibility could have also enabled the companies to cut costs fast enough to the keep the profit effect neutral in the crisis aftermath. Although it is beyond the scope of this study to fully explore the variations in the aftermath (which depend on factors ranging from the impact on imports and exports and the level of foreign currency-denominated debt to post-crisis fiscal and trilemma-related policies), such connections with prior studies, while undoubtedly speculative, serve to further support our model and empirical findings.

Finally, to complete our model, we include equity prices as an additional regressor. We define stock price movements as the percentage change in the country's equity index over the year. Table 7 presents the results. The negative predictive significance of the accounting accruals in the year prior to the crisis in low precision countries is robust to the inclusion of the stock price. The stock prices are not a predictor of crises.[28] But they fall significantly in the aftermath in both high and low precision countries, suggesting that the low precision countries do suffer a loss of investors, even though their immediate post-crisis profits themselves do not show any significant movement (after controlling for accruals). Our speculative conjecture is that investors appear to be unconvinced about these markets' future prospects, despite their firms' efforts to contain the losses.

D. Robustness Tests

We next conduct the following additional robustness tests:

(i) Our data do not account for crises that were deterred or did not happen even though they were theoretically likely. To partially account for this omission, we nominate the less severe crises as those falling into these

[28] Our estimation technique does not construct the composite signal z', but instead includes z and p separately. Table 7 indicates that z appears to be a stronger predictive signal than p.

categories. We repeat our analysis by redefining the crisis year indictor as 1 only if the year after the crisis saw an output loss for that country that was greater than the concurrent sample median (all the other crises thus become non-crises). We obtain similar results in Table A4. Accounting accruals in year -1 are significant negative predictors only in low precision countries. The aftermath results are similar to Table 6, Panel A.

(ii) The descriptive statistics for all the leading indicators are reported in Table A3, Panel B. Some leading indicators have extreme values. The extreme values for the currency overvaluation variable are from Indonesia and Mexico during periods of high inflation. The extreme values for the excess real M1 balances are due to the EU countries that experienced a discontinuity in the M2 measures in 1999. Our main results hold if we winsorize these indicators (Table A5).

(iii) We use an alternative measure of accounting precision based on a user perception of accounting information, as opposed to the properties of reported earnings. We construct an accounting precision measure based on the forecast frequency of financial analysts, who are key users of accounting information. Financial analysts collect, process, and most importantly, disseminate information about a firm to the public. As a result, prior literature argues that the number of analysts following a firm is indicative of the quality of the public information available about the firm (e.g., Lang and Lundholm 1996; Hong, Lim, and Stein 2000). We divide the sample into high and low precision countries using analyst following as the measure, and examine the predictive power of the realized accounting signals.

Table A6 lists the countries' new partition, which shows a considerable overlap with our existing partition. This congruence is additional validation for our partition approach. Table A6 also shows that the realized accounting accruals in the year prior to the crisis are a significantly lower only in countries with low analyst following (though the statistical significance is at the 10 percent level). Accruals in year -1 are insignificant in countries with high analyst following. The aftermath looks similar to Table 6, Panel A, though the joint and individual significances are somewhat different. This result suggests that our main findings mostly hold with user perception measures of accounting precision. In addition, this analysis also demonstrates both the importance and the empirical difficulties of identifying the multiplicity threshold correctly.

(iv) Finally, Table A7 shows that our main results are robust to switching from a probit to a logit regression model. Accounting accruals in the year prior to the crisis are significant negative predictors only in the low precision countries. The aftermath is similar to Table 6, Panel A as well. Thus, our results are not driven by the functional form of the binary choice model.

IV. Conclusion

Disagreements about basic macroeconomics paradigms (e.g., Solow 2010) suggest that macroeconomics is unlikely to converge on a unified theory of crisis: the underlying phenomena are too complex to be definitively abstracted. Our more modest goal is therefore to empirically show that the global-game coordination models are a viable abstraction of the true complex processes that precipitate crises, after controlling for previously posited determinants.

We build and test a global-game model in the context of accounting data and the "twin" currency and systematic banking crises, choices that we have justified at length in our paper. Our evidence that the pre-crisis accounting signals of fundamentals are significantly lower only in low precision countries is consistent with our model.

Our findings have two implications. First, as suggested by Summers (2000, p.10) and Rajan and Zingales (1998, p. 569), the application of accounting rules and principles to measure firm operations indeed appears to generate asset-pricing information relevant to macroeconomic phenomena (in our case crises). Second, as financial markets continue to gain prominence in macroeconomic research, global games offer an important insight: improvements in the public signals in such markets do not necessarily offer a monotone improvement in these markets' ability to allocate resources; investors can also get more unnecessarily "spooked." However, such non-convexities do not easily lend themselves to straightforward empirical analyses. It is our position that, in this "age of accounts" (to use Samuelson's (1970, Ch.5) felicitous phrase), innovative use of institutional data such as accounting has the power to overcome these empirical barriers.

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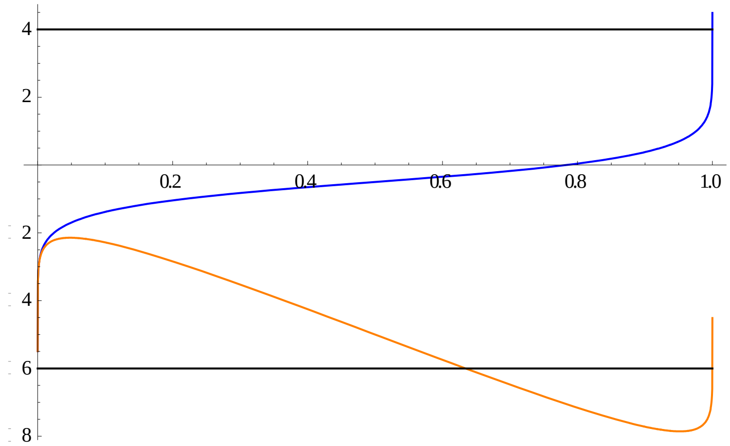
FIGURE 1 PLOT OF EQUATION (1)



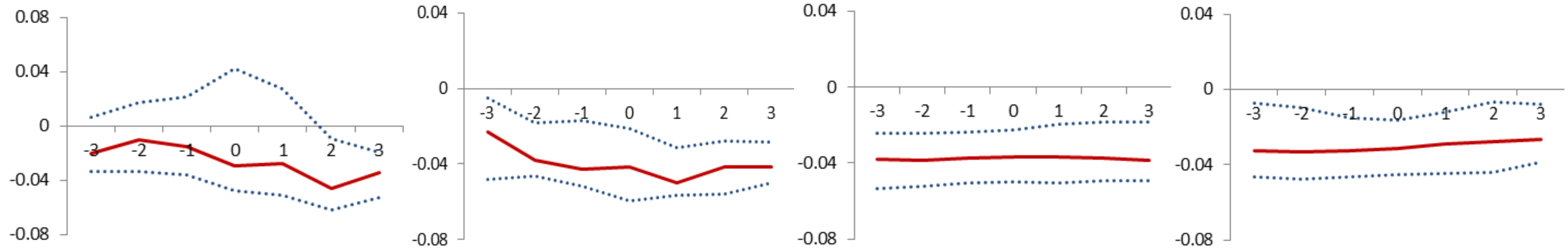
Notes: The x-axis is $\bar{\theta} \in [0,1]$. The two curves are $-\frac{\alpha_{z'}}{\sqrt{\alpha_x}}\bar{\theta} + \Phi^{-1}(\bar{\theta})$, the blue being the case when $\frac{\alpha_{z'}}{\sqrt{\alpha_x}} \leq \sqrt{2\pi}$, and orange when $\frac{\alpha_{z'}}{\sqrt{\alpha_x}} > \sqrt{2\pi}$. Note that both curves go to $-\infty,(+\infty)$ as $\bar{\theta} \to 0,(+1)$. The horizontal lines are $\sqrt{1+\frac{\alpha_{z'}}{\alpha_x}}\Phi^{-1}(1-c) - \frac{\alpha_{z'} z'}{\sqrt{\alpha_x}}$ for different values of *z*'.

FIGURE 2 REALIZED ACCOUNTING SIGNALS BEFORE AND AFTER 68 CRISIS EPISODES

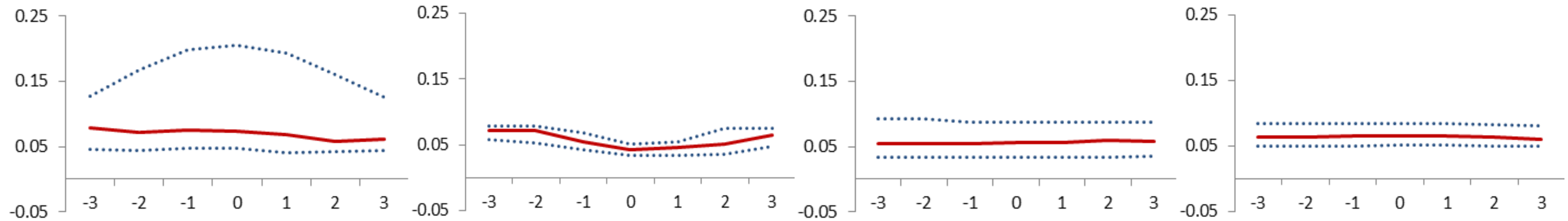
[C=COUNTRY, 17 COUNTRIES; T=YEAR, YEARS = 1983 – 2005]

Panel A: Accruals$_{c,t}$

Crisis years: High Precision Nations | *Crisis years: Low Precision Nations* | *Tranquil Years: High Precision Nations* | *Tranquil Years: Low Precision Nations*



Panel B: Profit$_{c,t}$



Notes: See Table 1 for crisis years and Table 4 for definitions of each accounting signal. Low and high accounting information quality countries are defined in Table 3. "Tranquil" years are all years that are not within 24 months before and after the start of a currency crisis. The horizontal axis represents the number of years before and after a crisis (or tranquil) year. The vertical axis represents the level of realized accounting signals. The solid line represents the country median of realized accounting signals before and after crisis (or tranquil) years. The bands represent the upper and lower quartiles of the realized accounting signal.

TABLE 1 CRISIS YEARS

Country	**Type of crisis**			
	Currency crises			Systemic Banking crises
	Financial Excess	Sovereign debt	Others (Fiscal deficit, Current account, Sudden stops)	
Argentina		1987		1985[a]
		1989		1989
		1990		1994
				2001
			2002	
Brazil		1983		
		1987		1985[a]
		1989		1990[b]
		1990		1994
	1999	1991		
Denmark			1993	1987[a]
Finland		1991		1991
		1992		
India				1993[b]
Indonesia	1983	1986		1992[a]
		1997		1997
		1998		
Italy	1990			
Japan				1997[b]
Malaysia				1985[a]
	1997			1997
	1998			
Mexico	1994			1992[a]
				1994[b]
Norway		1998	1986	1988[a]
		1999	1992	1991[b]
		2000		
Philippines	1983	1986		1983[b]
	1984	1997		1997[a]
South Korea				1997[b]
Spain	1992			
	1993			
Sweden		1992		1991
Thailand	1984	1997		1983
		1998	2000	1996
		1999		
Turkey			1994	1991[a]
			2001	1994[a]
				2000
Total # of crisis years	11	22	7	28

Notes: Crisis episodes are taken directly from the Excel supplement of Kaminsky (2006) available on-line (http://home.gwu.edu/~graciela/HOME-PAGE/RESEARCH-WORK/MAIN-PAGE/working-papers.htm), and from the systemic banking crises dataset of Laeven and Valencia (2008, Table 1). We include all crises from 1983, the beginning of our sample period. Crisis starting years are taken directly from the Excel supplement of Kaminsky (2006), column B and E. For the systemic banking crises episodes of Laeven and Valencia (2008), we use the starting dates provided in Table, column 2 of Laeven and Valencia (2008). There are two banking crises with discrepancies in dates across the two databases: Argentina in 1994 (1995 in Laeven and Valencia) and Thailand in 1996 (1997 in Laeven and Valencia). For the starting dates of these three crises, we follow the years from Kaminsky (2006).

[a] Systemic banking crisis years that appears only in Kaminsky (2006).

[b] Systemic banking crisis years that appears only in Laeven and Valencia (2008).

TABLE 2 INDIVIDUAL COUNTRIES' MEASURES OF ACCOUNTING SIGNAL PRECISION

(C=COUNTRY, F=FIRM, T=YEAR)

	Description	**Measure**
$AQ^1_{c,t}$ *Accruals quality*	Measures how well accruals flow into past, current, and future cash flow realizations (Source: Dechow and Dichev 2002)	$AQ^1_{c,t} = \sigma_f(\varepsilon_{c,t})$ $\text{Accruals}_{c,f,t} = \hat{\alpha}_{c,t} + \hat{\beta}^0_{c,t} \times \text{CFO}_{c,f,t-1} + \hat{\beta}^1_{c,t} \times \text{CFO}_{c,f,t} + \hat{\beta}^2_{c,t} \times \text{CFO}_{c,f,t+1} + \varepsilon_{c,f,t}$
$AQ^2_{c,t}$ *Smoothing*	Measures the extent to which accounting accruals offset cash flow shocks (Source: Francis et al. 2005)	$AQ^2_{c,t} = -Corr\left\{\Delta\left(\frac{Accruals_{c,f,t}}{TotalAsset_{c,f,t-1}}\right), \Delta\left(\frac{CFO_{c,f,t}}{TotalAsset_{c,f,t-1}}\right)\right\}$
$AQ^3_{c,t}$ *Accruals*	Level of accruals (Source: Sloan 1996)	$AQ^3_{c,t} = Median_f\left(\frac{Accruals_{c,f,t}}{TotalAsset_{c,f,t-1}}\right)$
$AQ^4_{c,t}$ *Absolute accruals*	Magnitude of accruals (Source: Leuz, Nanda, and Wysocki 2003)	$AQ^4_{c,t} = Median_f\left(\frac{\lvert Accruals\rvert_{c,f,t}}{\lvert CFO\rvert_{c,f,t}}\right)$
$AQ^5_{c,t}$ *Total accruals*	Level of total accruals (Source: Richardson et al. 2005)	$AQ^5_{c,t} = Median_f\left(\frac{TotalAccruals_{c,f,t}}{TotalAsset_{c,f,t-1}}\right)$
$AQ^6_{c,t}$ *Absolute total accruals*	Magnitude of total accruals (Source: Leuz, Nanda, and Wysocki 2003)	$AQ^6_{c,t} = Median_f\left(\frac{\lvert TotalAccurals\rvert_{c,f,t}}{\lvert CFO\rvert_{c,f,t}}\right)$
$AQ^i_{c,t,P}$ *i= 1..6*	Time averaged measure over a P-year rolling window	$AQ^i_{c,t,P} = \frac{1}{P}\sum_{p=1}^{P}(AQ^i_{c,t-p+1}), \forall i$
AQ^i_c *i= 1..6*	Per-country mean of each measure	$AQ^i_c = Mean_t\left(AQ^i_{c,t}\right)$

Notes: Each measure is defined such that a *lower* value represents *higher* accounting precision.

$Accruals_{c,f,t} = (\Delta CA_{c,f,t} - \Delta Cash_{c,f,t}) - (\Delta CL_{c,f,t} - \Delta STDebt_{c,f,t} - \Delta TaxPayable_{c,f,t}) - Depreciation_{c,f,t}$

$TotalAccruals_{c,f,t} = (\Delta TotalAsset_{c,f,t} - \Delta TotalLiability_{c,f,t}) - \Delta Cash_{c,f,t}$

$CFO_{c,f,t} = OperNI_{c,f,t} - Accruals_{c,f,t}$

TABLE 3 COUNTRIES' AVERAGE MEASURE OF ACCOUNTING PRECISION

(C=COUNTRY, 17 COUNTRIES, YEARS = 1983 TO 2005)

Panel A: Countries with high accounting precision

Country	# of years	# of firm-years	Level of accounting precision averaged over the sample period						Composite country index
			AQ_c^1	AQ_c^2	AQ_c^3	AQ_c^4	AQ_c^5	AQ_c^6	$= Mean_i\{Rank_c(AQ_c^i)\}$ where i = 1...6
Denmark	21	2,426	0.0512	0.8917	-0.0485	0.5567	0.0391	0.6339	5.2
Spain	21	1,804	0.0499	0.9340	-0.0369	0.4484	0.0588	0.6596	5.5
Norway	22	2,145	0.0621	0.6576	-0.0505	0.5585	0.0496	2.3362	6.5
Sweden	23	3,748	0.0519	0.8204	-0.0334	0.4701	0.0662	0.8025	6.5
Finland	21	1,948	0.0149	0.8963	-0.0567	0.6056	0.0594	0.6825	7.3
Mexico	21	2,112	0.0491	0.8299	-0.0138	0.4706	0.2293	1.5416	7.3
India	16	4,244	0.0519	0.7606	-0.0186	0.4488	0.0899	0.8172	7.5
Japan	21	23,738	0.0683	0.9854	-0.0276	0.5307	0.0264	0.7133	8.2

Panel B: Countries with low accounting precision

Country	# of years	# of firm-years	Level of accounting precision averaged over the sample period						Composite country index
			AQ_c^1	AQ_c^2	AQ_c^3	AQ_c^4	AQ_c^5	AQ_c^6	$= Mean_i\{Rank_c(AQ_c^i)\}$ where i = 1...6
Philippines	17	1,524	0.0474	0.8479	-0.0288	0.5072	0.0739	0.9692	8.3
Thailand	18	5,822	0.0581	0.9186	-0.0303	0.5720	0.0697	0.8302	8.3
Italy	23	4,162	0.0558	0.9073	-0.0492	0.6570	0.0621	0.9541	8.7
Indonesia	16	2,618	0.3759	0.9777	-0.0332	0.6353	0.0072	1.0548	10.7
Malaysia	23	5,786	0.0826	0.9230	-0.0130	0.5578	0.0527	1.0483	11.0
South Korea	20	6,567	0.0958	0.9494	-0.0262	0.6229	0.0557	0.9771	11.7
Argentina	19	662	0.0674	0.5242	0.3258	0.9821	2.4680	6.2378	13.2
Turkey	18	1,344	0.1818	0.7641	0.0643	0.6701	0.4428	2.0100	13.2
Brazil	18	5,393	0.3056	0.8400	-0.0206	0.6597	3.5114	4.4988	14.0

Notes: The variable definitions of accounting signal precision are in Table 2.

TABLE 4 DEFINITIONS AND DESCRIPTIVE STATISTICS OF ACCOUNTING SIGNALS

(C=COUNTRY, F=FIRM, T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Panel A: Definitions of accounting signals

Accounting Signal	Description	Measure
$Accruals_{c,t}$	Country median of firm level accruals scaled by lagged total assets	$accruals_{c,t} = Median_f \left(\frac{Operating\ Accruals_{c,f,t}}{TotalAssets_{c,f,t-1}} \right)$
$Profitability_{c,t}$	Country median of firm level net operating income scaled by lagged total assets	$profitability_{c,t} = Median_f \left(\frac{NI_{c,f,t}}{TotalAssets_{c,f,t-1}} \right)$

Notes:

$$Operating\ Accruals_{c,f,t} = \Delta Current\ operating\ asset_{c,f,t} - \Delta Current\ operating\ liability_{c,f,t} - Depreciation_{c,f,t}$$

$$= (\Delta Current\ Asset_{c,f,t} - \Delta Cash_{c,f,t}) - (\Delta Current\ Liability_{c,f,t} - \Delta STDebt_{c,f,,t} - \Delta TaxPayable_{c,f,t}) - Depreciation_{c,f,t}$$

$NI_{c,f,t}$ = Net operating income.

Panel B: Descriptive statistics of accounting signals

Variables	N	Mean	Std dev.	1 percentile	25 percentile	50 percentile	75 percentile	99 percentile
$Accruals_{c,t}$	311	(0.006)	0.268	(0.116)	(0.049)	(0.033)	(0.014)	0.201
$Profitability_{c,t}$	321	0.087	0.131	(0.004)	0.043	0.062	0.089	0.513

Panel C: Correlation of accounting signals and leading indicators

	$D\_crisis_{c,t}$	$Accruals_{c,t}$	$Profitability_{c,t}$
$D\_crisis_{c,t}$	1.00		
$Accruals_{c,t}$	0.19	1.00	
$Profitability_{c,t}$	0.17	0.63	1.00

Notes: Panel C displays all the pairwise correlation coefficients between accounting signals and leading indicators. Refer to Table A2 and Panel A for the definitions of the leading indicator variables and accounting signals.

TABLE 5 COMBINED SAMPLE ANALYSIS OF CRISES USING REALIZED ACCOUNTING SIGNALS

(C=COUNTRY; T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{2} \beta^{i} \times AccountingSignal^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

		Prior period [-n =-2]		*Prior period* [-n =-1]		*Concurrent* [-n =0]	
		coefficient	(se)	coefficient	(se)	coefficient	(se)
Table 4's Realized accounting signals ($= \beta^{i}$)							
Accruals$_{c,t}$		-0.602	(0.52)	-2.268	(1.39)	1.507*	(0.90)
Profitability$_{c,t}$		0.428	(1.24)	0.925	(1.75)	-5.215*	(3.05)
F- test [*P-value*]:		$\chi^2(2)$ =1.36 [0.505]		$\chi^2(2)$ =2.66 [0.264]		$\chi^2(2)$=3.58 [0.167]	
Indicator (crisis within last 3 yrs)	-	0.281*	(0.15)	-0.103	(0.13)	-0.188	(0.18)
Table A2's Prior literature's leading indicators and time trend ($= \gamma^{k}$)							
Over-valuation$_{c,t}$	-	-0.004**	0.00	-0.001***	0.00	-0.000***	0.00
Imports$_{c,t}$	+	0.003	(1.09)	0.621	(0.55)	-2.022*	(1.18)
Exports$_{c,t}$	-	-0.842	(1.06)	-0.460	(1.10)	1.184	(1.09)
Foreign exchange reserve$_{c,t}$	-	0.513**	(0.23)	0.224	(0.25)	-1.210***	(0.43)
M2/foreign exchange$_{c,t}$ reserve$_{c,t}$	+	-0.115***	(0.04)	0.173*	(0.09)	0.276***	(0.06)
Real interest rate differential$_{c,t}$	+	1.021	(2.27)	-1.908	(1.86)	-4.997***	(1.77)
Short term debt/reserves$_{c,t}$	+	-0.011	(0.12)	0.137	(0.17)	0.244*	(0.13)
Industry production$_{c,t}$	-	-0.347	(2.50)	-9.486***	(2.54)	-16.594***	(3.59)
Stock prices$_{c,t}$	-	-0.721*	(0.39)	-0.161	(0.56)	-1.019**	(0.49)
M2 multiplier$_{c,t}$	+	-0.248	(0.48)	-0.326	(0.48)	-0.721*	(0.38)
Domestic credit/GDP$_{c,t}$	+	2.120***	(0.74)	1.554**	(0.78)	-3.558**	(1.44)
Domestic real interest rate$_{c,t}$	+	1.052	(2.27)	-1.893	(1.85)	-4.953***	(1.76)
Commercial bank deposits$_{c,t}$	-	0.680	(1.09)	-2.271**	(0.97)	1.619	(2.18)
Lending/deposit interest rate$_{c,t}$	+	-0.211	(0.15)	-0.015	(0.02)	-0.004	(0.02)
Excess real M1 balances$_{c,t}$	+	0.000	0.00	0.002***	0.00	0.002***	0.00
G7 output$_{t}$	-	-0.590	(0.61)	-0.873	(0.69)	1.002*	(0.54)
US interest rate$_{t}$	+	37.902***	(12.26)	4.721	(17.08)	-1.670	(15.18)
Oil prices$_{t}$	+	0.901*	(0.53)	1.545**	(0.70)	0.157	(0.57)
Year trend$_{t}$		-0.057**	(0.02)	-0.091***	(0.03)	-0.127***	(0.03)
Country Fixed Effects		Yes		Yes		Yes	
Standard Error clustering on year		Yes		Yes		Yes	
# country-years		277		294		311	
Mc Fadden's R^2		0.278		0.304		0.443	
Mc Fadden's R^2 (excluding accounting signals)		0.275		0.288		0.422	

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. *Indicator (crisis within last 3 yrs)* is an indicator variable that takes a value of one if there was a crisis that occurred within the last three calendar years, and zero otherwise. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE 6 ANALYSIS OF CRISES USING PRIOR OR CONCURRENT ACCOUNTING SIGNALS: BY LEVEL OF ACCOUNTING PRECISION

(C=COUNTRY, T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Panel A: Using Accruals and Profitability

Model: $D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{2} \beta^i \times AccountingSignal^i_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
	Prior period [-n =-2]		*Prior period* [-n =-1]		*Concurrent* [-n =0]	
	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
Table 4's Realized accounting signals (= β^i)						
$Accruals_{c,t}$ β^1	20.245^{***}	-4.290	-0.449	-2.833^{**}	-35.060^{***}	4.232^{***}
	(7.42)	(5.09)	(6.72)	(1.26)	(13.46)	(1.19)
$Profitability_{c,t}$ β^2	-6.313	4.065	-16.924	2.340	-179.467^{***}	1.765
	(13.65)	(2.72)	(13.08)	(1.51)	(39.69)	(4.48)
F- test: β^1, β^2=0 [*P-value*]:	$\chi^2(2) = 8.98$ [0.001]	$\chi^2(2) = 2.63$ [0.269]	$\chi^2(2) = 1.90$ [0.387]	$\chi^2(2) = 6.30$ [0.043]	$\chi^2(2) = 22.51$ [<0.001]	$\chi^2(2) = 12.73$ [0.002]
Leading indicators from Table A2 and time trend	Included	Included	Included	Included	Included	Included
Indicator (crisis within last 3 yrs)	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering on year	Yes	Yes	Yes	Yes	Yes	Yes
# country-years	135	142	143	151	151	160
Mc Fadden's R^2	0.424	0.463	0.389	0.388	0.789	0.636
Mc Fadden's R^2 (excluding accounting signals)	0.386	0.438	0.376	0.353	0.642	0.579

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 3 for definitions of the country samples with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Standard errors clustered by year are in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE 6 ANALYSIS OF CRISES USING PRIOR OR CONCURRENT ACCOUNTING SIGNALS: BY LEVEL OF ACCOUNTING PRECISION (CONTINUED)

(C=COUNTRY, T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Panel B: Using Accruals only

Model: $D\_Crisis_{c,t} = \alpha + \beta^{i} \times AccountingSignal^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
	Prior period [-n =-2]		*Prior period* [-n =-1]		*Concurrent* [-n =0]	
	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
Table 4's Realized accounting signals (= β^{i})						
$Accruals_{c,t}$ β^{1}	19.208**	-0.937	0.294	-2.475*	-13.208	4.365***
	(7.93)	(1.05)	(6.21)	(1.32)	(8.37)	(1.28)
Leading indicators from Table A2 and time trend	Included	Included	Included	Included	Included	Included
Indicator (crisis within last 3 yrs)	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering on year	Yes	Yes	Yes	Yes	Yes	Yes
# country-years	135	142	143	151	151	160
Mc Fadden's R^2	0.423	0.442	0.376	0.378	0.649	0.635
Mc Fadden's R^2 (excluding accounting signals)	0.386	0.438	0.376	0.353	0.642	0.579

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 3 for definitions of the country samples with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Standard errors clustered by year are in parentheses. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE 7: ANALYSIS OF CRISES USING ACCOUNTING SIGNALS AND EQUITY PRICE

(C=COUNTRY; T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Model:

$$D\_Crisis_{c,t} = \alpha + \beta^{1} \times Stockprice^{i}_{c,t-n} + \sum_{i=1}^{2} \beta^{i} \times AccountingSignal^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

		(1)	(2)	(3)	(4)
		Prior period [-n =-1]		*Concurrent* [-n =0]	
		High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
		coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
Stock price$_{c,t}$	β^1	0.204	-1.275	-6.797***	-4.021**
		(0.69)	(1.00)	(2.58)	(1.97)
Accruals$_{c,t}$	β^2	-0.449	-2.833**	-35.060***	4.232***
		(6.72)	(1.26)	(13.46)	(1.19)
Profitability$_{c,t}$	β^3	-16.924	2.340	-179.467***	1.765
		(13.08)	(1.51)	(39.69)	(4.48)
F- test: β^1, $\beta^2 = 0$ [*P-value*]:		$\chi^2(3) = 2.26$ [0.520]	**$\chi^2(3) = 6.68$ [0.083]**	**$\chi^2(3) = 23.14$ [<0.001]**	**$\chi^2(3) = 27.37$ [<0.001]**
Leading indicators from Table A2 and time trend		Included	Included	Included	Included
Indicator (crisis within last 3 yrs)		Yes	Yes	Yes	Yes
Country Fixed Effects		Yes	Yes	Yes	Yes
SE clustering on year		Yes	Yes	Yes	Yes
# country-years		143	131	151	139
Mc Fadden's R^2		0.389	0.370	0.769	0.683

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Stock price change is the percent change in equity index (IFS.62.ZF). Refer to Table 3 for a definition of the country sample with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Standard errors clustered by year are in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

Appendix

TABLE A1: CRISIS STARTING YEARS AND NUMBER OF PUBLIC FIRMS

Currency crises
Systemic banking crises
Currency & systemic banking crises

Number of public firm-year observations

Year	Argentina	Brazil	Denmark	Finland	India	Indonesia	Italy	Japan	Malaysia	Mexico	Norway	Philippines	South Korea	Spain	Sweden	Thailand	Turkey
1983	0	0	0	0	0	0	2	0	1	0	0	0	0	0	1	0	0
1984	0	0	0	6	0	0	6	0	3	0	1	0	0	0	4	0	0
1985	0	0	4	7	0	0	8	2	5	7	7	0	0	2	4	0	0
1986	0	0	4	10	0	0	15	11	7	7	12	0	1	3	8	0	0
1987	2	0	5	13	0	0	39	18	10	12	16	0	1	8	12	0	0
1988	6	15	36	38	0	0	186	37	35	38	66	0	13	54	85	4	2
1989	7	99	96	76	0	0	200	142	43	47	82	5	73	71	113	8	10
1990	7	113	125	90	6	2	207	614	50	48	97	5	106	76	145	21	18
1991	7	111	127	90	6	10	208	933	55	47	97	10	99	86	149	42	21
1992	16	148	134	90	32	86	208	1057	106	77	96	36	100	89	154	141	24
1993	21	151	137	89	137	94	200	1085	135	90	90	46	111	92	160	231	28
1994	26	162	143	92	156	101	191	1127	138	105	101	52	165	92	171	301	40
1995	30	197	143	93	175	106	200	1182	156	114	97	57	194	93	184	318	38
1996	28	253	141	93	256	147	195	1219	234	112	97	82	218	97	184	346	41
1997	37	256	171	116	281	155	210	1255	267	120	165	87	259	119	236	372	53
1998	39	278	175	131	298	161	231	1288	304	125	172	88	299	116	270	385	73
1999	49	319	167	130	305	163	247	1789	309	164	156	103	383	117	265	375	89
2000	60	571	154	126	309	193	262	1791	342	170	128	113	649	116	270	375	111
2001	66	561	145	134	350	262	268	1863	548	172	129	152	667	119	263	517	131
2002	68	541	140	132	412	282	262	2019	671	173	124	165	731	114	253	532	140
2003	68	529	137	128	437	286	268	2035	710	167	129	175	814	113	261	585	169
2004	64	541	124	132	510	284	276	2109	794	162	141	172	837	117	279	631	179
2005	61	548	118	132	574	286	273	2162	863	155	142	176	847	110	277	638	177
Total # of firm-years	662	5393	2426	1948	4244	2618	4162	23738	5786	2112	2145	1524	6567	1804	3748	5822	1344
# of crisis years (sum of shaded cells)	7	8	2	2	1	5	1	1	3	2	7	4	1	2	2	7	4

Notes: Figures in the table represent the number of public firm observations in each country-year with financial data (total asset, net income from operations, current assets and current liabilities) available in Thomson Datastream. Shaded cells represent the year of the beginning of a crisis as described in Table 1.

TABLE A2: DEFINITIONS AND DESCRIPTIVE STATISTICS OF PRIOR LITERATURE'S LEADING INDICATORS

(C=COUNTRY, T=YEAR)

Panel A: Definition of leading indicators

Category	Indicator (Variable name)	Definition	Measure & data source	Predicted association with crisis	
Current account	Deviation from the expected real exchange rate ($XS\_realEX_{c,t}$)	Deviation of real exchange rate from time (year) trend regression	- residual value from time trend equation estimated by each country - real exchange rate= nominal bilateral exchange rate* (IFS.00ae) (US CPI/domestic CPI) (IFS.64.ZF)	Over-valuation of local currency is linked to currency crisis	(-)
	Imports ($\Delta Imports_{c,t}$)	Percent change in imports	- imports (IFS.70.ZF)	Weak external sector	(+)
	Exports ($\Delta Exports_{c,t}$)	Percent change in exports	- exports (IFS.71.ZF)	Weak external sector	(-)
Capital account	Foreign exchange reserve ($\Delta FXreserve_{c,t}$)	Percent change in foreign exchange reserve	- foreign exchange reserve = Total reserve minus gold (IFS.1L.ZF)	Loss of foreign reserve is a characteristic of currency crisis; Krugman (1979)	(-)
	M2/foreign exchange reserve ($\Delta M2\_FXreserve_{c,t}$)	Percent change in M2/foreign exchange reserve	- M2= Quasi money (IFS.35.ZF) - foreign exchange reserve (IFS.1L.ZF)	Expansionary monetary policy and/or sharp decline in reserve is associated with a currency crisis	(+)
	Real interest rate differential ($interest\_diff_{c,t}$)	Level of foreign and domestic interest rate differential	- foreign real interest rate = US lending interest rate – US inflation rate calculated from US CPI - domestic real interest rate = lending interest (IFS.60P.ZF) – domestic inflation rate	High world interest rate can lead to reversal of capital flow	(+)
	Short term debt/reserves ($\Delta ST\_debt_{c,t}$)	Percent increase in ST debt	- ST debt = debt with maturity less than 1 year (from BIS database) - foreign exchange reserve = Foreign exchange (IFS.1L.D.ZF)	Increase in ST debt is associated with currency crisis	(+)
Real sector	Industry production ($\Delta Output_{c,t}$)	Percent change in output	- industry production (IFS.66A.ZF)	Recessions often precede crises	(-)
	Stock price ($\Delta Equity_{c,t}$)	Percent change in equity index	- equity indices (IFS.62.ZF)	Burst of asset bubble often precedes currency crisis	(-)

* The nominal exchange rate between the currencies of domestic countries and the U.S., expressed as the number of US currency units per domestic currency unit.

TABLE A2: DEFINITIONS AND DESCRIPTIVE STATISTICS OF PRIOR LITERATURE'S LEADING INDICATORS (CONTINUED)

Domestic financial	M2 multiplier, ($\Delta M2\_multiplier_{c,t}$)	Percent change in M2 multiplier	- M2 multiplier = M2 / Base money - M2= Money (IFS.34.ZF) + Quasi money (IFS.35.ZF) - base money (IFS.14.ZF)	Rapid growth of credit	(+)
	Domestic credit/GDP, ($\Delta Domes\_credit_{c,t}$)	Percent change in domestic credit	- domestic credit (IFS.32.ZF) - GDP (IFS.99B.ZF)	Credit expands prior to crisis	(+)
	Domestic real interest rate ($Dom\_real\_interest_{c,t}$)	Domestic real interest rate	- real exchange rate = deposit interest rate (IFS.60L.ZF) – inflation - inflation$_{c,t}$=(CPI$_{c,t}$-(CPI$_{c,t-1}$))/(CPI$_{c,t-1}$) (IFS.64.ZF)	Higher real interest rate can signal liquidity crunch or may have been increased to defend against speculative attacks	(+)
	Commercial bank deposits ($\Delta comm\_deposit_{c,t}$)	Percent change in commercial bank deposits deflated by CPI	- commercial bank deposits = demand deposits (IFS.24.ZF) + other deposits (IFS.25.ZF) - CPI (IFS.64.ZF)	Loss of deposits occurs as crisis unfolds	(-)
	Lending/deposit interest rate ($\Delta LD\_ratio_{\ c,t}$)	Level of lending to deposit ratio	- lending interest (IFS.60P.ZF) - deposit interest (IFS.60L.ZF)	Lending rates tend to rise prior to a crisis due to a decline in loan quality	(+)
	Excess real M1 balances ($XS\_real\_MI_{c,t}$)	Ml deflated by consumer prices less estimated demand for money	- each country's money demand equation is estimated as a function of real GDP, domestic CPI, and time (=year) - M1 = Money (IFS.35.ZF) - CPI (IFS.64.ZF) - real GDP= GDP (IFS.99B.P)	Loose monetary policy can lead to a currency crisis	(+)
Global	G7 output ($G7\_GDP\_growth_t$)	Percent change in Changes in G7's average real GDP growth	- weighted average of G7 real GDP growth - real GDP= GDP (IFS.99B.ZF) / CPI (IFS.64.ZF)	Foreign recessions often precede crises	(-)
	U.S. interest rate ($US\_real\_interest_t$)	Changes in level of US real interest rate	- real interest rate = nominal interest (IFS.60L.ZF) – inflation rate - inflation=(CPI-lag(CPI))/(lagCPI) (IFS.64.ZF)	Increase in foreign interest associated with capital outflows	(+)
	Oil prices (Oil_price_t)	Percent change in oil price	- oil price (IFS.0017.AAZ)	High oil prices are associated with recessions	(+)

Notes: All leading indicator variables are taken directly from the Edison (2003) Appendix A. All leading indicators are measured as annual percentage changes, except (a) interest rate measured as changes over the previous twelve months, (b) real exchange rate as a deviation from time trend, and (c) excess M1 as residuals from the money demand equation. Source: International Financial Statistics (IFS) and other sources as noted.

TABLE A2: DEFINITIONS AND DESCRIPTIVE STATISTICS OF PRIOR LITERATURE'S LEADING INDICATORS (CONTINUED)

(C=COUNTRY, T=YEAR)

Panel B: Descriptive statistics of leading indicators

Variables		**N**	**Mean**	**Stn dev.**	**1 percent**	**20 percent**	**Median**	**75 percent**	**20 percent**
Current Account	Over-valuation$_{c,t}$	339	(32.0)	673.7	(3626)	(1.46)	(0.26)	1.11	2,417†
	Imports$_{c,t}$	339	0.10	0.16	(0.31)	0.00	0.10	0.18	0.54
	Exports$_{c,t}$	339	0.10	0.11	(0.13)	0.02	0.09	0.17	0.38
Capital Account	Foreign exchange reserve$_{c,t}$	339	0.19	0.44	(0.58)	(0.02)	0.14	0.30	1.97
	M2/foreign exchange$_{c,t}$	339	0.67	5.90	(0.64)	(0.12)	0.00	0.18	18.21
	Real interest rate differential$_{c,t}$	339	(0.90)	8.96	(30.95)	(0.04)	(0.01)	0.01	0.41
	Short term debt/reserves$_{c,t}$	339	0.10	0.56	(0.67)	0.00	0.00	0.00	2.72
Real Sector	Industry production$_{c,t}$	339	0.04	0.06	(0.09)	0.00	0.03	0.07	0.21
	Stock prices$_{c,t}$	339	0.14	0.44	(0.37)	(0.02)	0.00	0.25	1.11
Domestic Financial	M2 multiplier$_{c,t}$	339	(0.01)	0.25	(0.91)	(0.06)	0.00	0.05	0.78
	Domestic credit/GDP$_{c,t}$	339	0.00	0.16	(0.54)	(0.03)	0.01	0.05	0.41
	Domestic real interest rate$_{c,t}$	339	0.90	8.96	(0.37)	0.00	0.02	0.05	30.99
	Commercial bank deposits$_{c,t}$	339	0.07	0.33	(0.50)	0.00	0.04	0.11	0.69
	Lending/deposit interest rate$_{c,t}$	339	2.28	4.60	0.00	1.22	1.53	2.14	29.36
	Excess real M1 balances$_{c,t}$	339	(7.37)	229	(884.5)	(6.20)	(0.01)	0.34	1,185††
External	G7 output$_t$	339	(0.01)	0.25	(0.41)	(0.19)	(0.03)	0.09	0.56
	US interest rate$_t$	339	(0.00)	0.01	(0.02)	(0.01)	(0.00)	0.01	0.01
	Oil prices$_t$	339	0.07	0.25	(0.48)	(0.12)	0.03	0.28	0.57

† Extreme values consist of observations from Indonesia and Mexico during periods of high inflation.
†† Extreme values are driven by EU countries that have discontinuity in M2 measures post year 1999.

TABLE A3: MARGINAL EFFECTS AVERAGED OVER THE SAMPLE

(C=COUNTRY; T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Panel A: Analysis of Crises Using Accounting Signals in Table 5

		Prior period [-n =-2]		*Prior period* [-n =-1]		*Concurrent* [-n =0]	
		$\frac{dF}{dX}$	Δ method se	$\frac{dF}{dX}$	Δ method se	$\frac{dF}{dX}$	Δ method se
Table 4's Realized accounting signals							
$\text{Accruals}_{c,t}$		-0.092	(0.07)	-0.348*	(0.19)	0.188*	(0.11)
$\text{Profitability}_{c,t}$		0.065	(0.15)	0.142	(0.23)	-0.652*	(0.36)
F- test [*P-value*]:		χ^2 (2) =1.94 [0.379]		χ^2 (2) =3.43 [0.180]		χ^2(2)=3.97** [0.138]	
Indicator (crisis within last 3 yrs)	-	0.044*	(0.02)	-0.016	(0.02)	-0.023	(0.02)
Table A2's Prior literature's leading indicators and time trend							
$\text{Over-valuation}_{c,t}$	-	-0.001***	(0.00)	-0.0001**	(0.00)	-0.00004**	(0.00)
$\text{Imports}_{c,t}$	+	0.001	(0.14)	0.095	(0.07)	-0.253*	(0.13)
$\text{Exports}_{c,t}$	-	-0.128	(0.13)	-0.071	(0.15)	0.148	(0.13)
Foreign exchange $\text{reserve}_{c,t}$	-	0.078**	(0.03)	0.034	(0.03)	-0.151***	(0.05)
M2/foreign $\text{exchange}_{c,t}$ $\text{reserve}_{c,t}$	+	-0.018***	0.00	0.027**	(0.01)	0.035***	(0.01)
Real interest rate $\text{differential}_{c,t}$	+	0.156	(0.28)	-0.293	(0.26)	-0.624***	(0.21)
Short term debt/$\text{reserves}_{c,t}$	+	-0.002	(0.01)	0.021	(0.02)	0.030**	(0.02)
Industry $\text{production}_{c,t}$	-	-0.053	(0.31)	-1.457***	(0.37)	-2.073***	(0.38)
Stock $\text{prices}_{c,t}$	-	-0.110**	(0.05)	-0.025	(0.07)	-0.127**	(0.06)
M2 $\text{multiplier}_{c,t}$	+	-0.038	(0.06)	-0.050	(0.06)	-0.090**	(0.05)
Domestic credit/$\text{GDP}_{c,t}$	+	0.323***	(0.09)	0.239**	(0.11)	-0.444***	(0.16)
Domestic real interest $\text{rate}_{c,t}$	+	0.160	(0.28)	-0.291	(0.26)	-0.619***	(0.21)
Commercial bank $\text{deposits}_{c,t}$	-	0.104	(0.14)	-0.349**	(0.14)	0.202	(0.25)
Lending/deposit interest $\text{rate}_{c,t}$	+	-0.032*	(0.02)	-0.002	0.00	-0.001	0.00
Excess real M1 $\text{balances}_{c,t}$	+	0.000	0.00	0.0004***	(0.00)	0.00017***	(0.00)
G7 output_{t}	-	-0.090	(0.08)	-0.134	(0.09)	0.125**	(0.06)
US interest rate_{t}	+	5.779***	(1.41)	0.725	(2.27)	-0.209	(1.74)
Oil prices_{t}	+	0.137**	(0.07)	0.237***	(0.09)	0.020	(0.07)
Year trend_{t}		-0.009***	(0.00)	-0.134	(0.09)	-0.016***	(0.00)
Country Fixed Effects		Yes		Yes		Yes	
Standard Error clustering on year		Yes		Yes		Yes	
# country-years		277		294		311	
Mc Fadden's R^2		0.278		0.304		0.443	
Mc Fadden's R^2 (excluding accounting signals)		0.275		0.288		0.422	

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. *Indicator (crisis within last 3 yrs)* is an indicator variable that takes a value of one if there was a crisis that occurred within the last three calendar years, and zero otherwise. Reported coefficients represent the marginal effect averaged over all observations. Standard errors in parentheses are obtained using the delta method. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE A3: MARGINAL EFFECTS AVERAGED OVER THE SAMPLE (CONTINUED)

(C=COUNTRY, T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Panel B: Analysis of Crises Using Accounting Signals in Table 6 Panel A

Model: $D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{2} \beta^{i} \times AccountingSignal^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
	Prior period [-n =-2]		*Prior period* [-n =-1]		*Concurrent* [-n =0]	
	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)
Table 4's Realized accounting signals						
$Accruals_{c,t}$	1.593***	-0.419	-0.066	-0.346**	-0.878**	0.332***
	(0.45)	(0.41)	(0.84)	(0.15)	(0.34)	(0.08)
$Profitability_{c,t}$	-0.497	0.397*	-2.502	0.286**	-4.492***	0.138
	(0.88)	(0.22)	(2.86)	(0.14)	(0.98)	(0.32)
Leading indicators from Table A2 and time trend	Included	Included	Included	Included	Included	Included
Indicator (crisis within last 3 yrs)	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering on year	Yes	Yes	Yes	Yes	Yes	Yes
# country-years	135	142	143	151	151	160
Mc Fadden's R^2	0.424	0.463	0.389	0.388	0.789	0.636
Mc Fadden's R^2 (excluding accounting signals)	0.386	0.438	0.376	0.353	0.642	0.579

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 3 for definitions of the country samples with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Reported coefficients represent the marginal effect averaged over all observations. Standard errors in parentheses are obtained using the delta method. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE A3: MARGINAL EFFECTS AVERAGED OVER THE SAMPLE (CONTINUED)

(C=COUNTRY, T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Panel C: Analysis of Crises Using Accruals in Table 6 Panel B

Model: $\mathrm{D\_Crisis}_{c,t} = \alpha + \beta^{i} \times \mathrm{AccountingSignal}^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^{k} \times \mathrm{LeadingIndicators}_{c,t-n} + \varepsilon_{c,t}$

	(1)	(2)	(3)	(4)	(5)	(6)
	Prior period [-n =-2]		*Prior period* [-n =-1]		*Concurrent* [-n =0]	
	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)	$\frac{dF}{dX}$ (Δ method se)
Table 4's Realized accounting signals						
$\text{Accruals}_{c,t}$	1.536***	-0.937	0.042	-0.347**	-0.805**	0.345***
	(0.47)	(1.05)	(0.77)	(0.18)	(0.45)	(0.08)
Leading indicators from Table A2 and time trend	Included	Included	Included	Included	Included	Included
Indicator (crisis within last 3 yrs)	Yes	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering on year	Yes	Yes	Yes	Yes	Yes	Yes
# country-years	135	142	143	151	151	160
Mc Fadden's R^2	0.424	0.463	0.389	0.388	0.789	0.636
Mc Fadden's R^2 (excluding accounting signals)	0.386	0.438	0.376	0.353	0.642	0.579

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 3 for definitions of the country samples with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Reported coefficients represent the marginal effect averaged over all observations. Standard errors in parentheses are obtained using the delta method. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE A4: ANALYSIS OF 33 SEVERE CRISES USING ACCOUNTING SIGNALS

Model:

$$D\_SevereCrisis_{c,t} = \alpha + \sum_{i=1}^{2} \beta^i \times AccountingSignal^i_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

	(1)	(2)	(3)	(4)
	Prior period [-n =-1]		*Concurrent* [-n =0]	
	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
Table 4's Realized accounting signals (= β^i)				
$Accruals_{c,t}$ β^1	-0.449	-2.833**	-35.060***	4.232***
	(6.72)	(1.26)	(13.46)	(1.19)
$Profitability_{c,t}$ β^2	-16.924	2.340	-179.467***	1.765
	(13.08)	(1.51)	(39.69)	(4.48)
F- test: β^1, $\beta^2 = 0$ [*P-value*]:	$\chi^2(2) = 1.90$ [0.387]	**$\chi^2(2) = 6.30$ [0.043]**	**$\chi^2(2) = 22.51$ [<0.001]**	**$\chi^2(2) = 12.73$ [0.002]**
Leading indicators from Table A2 and time trend	Included	Included	Included	Included
Indicator (crisis within last 3 yrs)	Yes	Yes	Yes	Yes
Country Fixed Effects	No	No	No	No
SE clustering on year	Yes	Yes	Yes	Yes
# country-years	143	151	151	160
Mc Fadden's R^2	0.389	0.388	0.789	0.636

Notes: $D\_Severe\_Crisis_{c,t}$ is an indicator variable indicating a severe crisis year. Severe crisis is defined as a crisis year if the country's output loss in the subsequent year exceeds that year's sample median. subsequent year of the crisis. See Table 1 for crisis years. Refer to Table 3 for a definition of the country sample with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Standard errors clustered by year are in parentheses. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE A5: ADJUSTING FOR LEADING INDICATORS WITH EXTREME VALUES

(C=COUNTRY; T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{2} \beta^i \times AccountingSignal^i_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^k \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

		(1)	(2)	(3)	(4)
		Prior period [-n =-1]		*Concurrent* [-n =0]	
		High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
		coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
Table 4's Realized accounting signals (= β^i)					
Accruals$_{c,t}$	β^1	-3.281	-3.012**	-43.928***	5.046***
		(7.34)	(1.35)	(13.55)	(1.19)
Profitability$_{c,t}$	β^2	-11.936	2.957*	-195.179***	2.268
		(12.78)	(1.53)	(50.32)	(4.43)
F- test: β^1, $\beta^2 = 0$ [*P-value*]:		χ^2(2) = 1.65 [0.437]	**χ^2(2) = 6.26 [0.044]**	**χ^2(2) = 17.70 [<0.001]**	**χ^2(2) = 18.70 [<0.001]**
Over-valuation_w		-0.002	-0.008***	0.035	-0.008***
		(0.02)	(0.00)	(0.03)	(0.00)
XS real M1 balances_w		0.021**	0.001	0.011**	-0.015***
		(0.01)	(0.00)	(0.01)	(0.00)
Leading indicators from Table A2 and time trend		Included	Included	Included	Included
Indicator (crisis within last 3 yrs)		Yes	Yes	Yes	Yes
Country Fixed Effects		Yes	Yes	Yes	Yes
SE clustering on year		Yes	Yes	Yes	Yes
# country-years		143	151	151	160
Mc Fadden's R^2		0.394	0.408	0.794	0.634

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 3 for a definition of the country sample with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. We winzorize the two leading indicator variables with extreme values: Over-valuation and XS real M1 balances. *Over-valuation_w* is the deviation from the expected real exchange rate leading indicator variable winzorized at 3 percent. XS real M1 balances_w is the Excess real M1 balance leading indicator variable winzorized at 3 percent. Standard errors clustered by year are in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE A6: ANALYSIS OF CRISES USING ALTERNATIVE USER-BASED MEASURE OF ACCOUNTING PRECISION

(C=COUNTRY; T=YEAR, 17 COUNTRIES, YEARS = 1983 – 2005)

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{2} \beta^{i} \times AccountingSignal^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18} \gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{C_H} = 1$: if country rank of accounting precision exceeds the sample median, 0 otherwise.

$I_{C_L} = 1$: if country rank of accounting precision is the sample median, 0 otherwise.

		(1)	(2)	(3)	(4)
		Prior period [-n =-1]		*Concurrent* [-n =0]	
		High analyst following countries	Low analyst following countries	High analyst following countries	Low analyst following countries
		coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
Accruals$_{c,t}$	β^1	-9.215	-2.692*	18.838	5.147***
		(11.30)	(1.39)	(15.64)	(1.34)
Profitability$_{c,t}$	β^2	-1.185	2.466*	-190.159	-1.772
		(22.68)	(1.49)	(128.67)	(3.02)
F- test: β^1, $\beta^2 = 0$ [*P-value*]:		$\chi^2(2) = 0.81$ [0.669]	$\chi^2(2) = 4.26$ [0.12]	**χ^2 (2) = 6.64 [0.036]**	**χ^2 (2) = 17.30 [<0.001]**
Leading indicators from Table A2 and time trend		Included	Included	Included	Included
Indicator (crisis within last 3 yrs)		Yes	Yes	Yes	Yes
Country Fixed Effects		Yes	Yes	Yes	Yes
SE clustering on year		Yes	Yes	Yes	Yes
# country-years		105	189	111	200
Adjusted R^2		0.561	0.349	0.691	0.562

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 4 and Table A2 for definitions of the accounting signals and leading indicator variables. Countries with high and low accounting precision are partitioned using the median analysts following from I/B/E/S. Analyst following is defined as the median scaled by price (see Li, Lehavy, and Merkley 2011) in each country-year. We average the ranks for each country-year over the sample period starting from the earliest available year. Our high precision countries are: Spain, Finland, Italy, Sweden, Norway, Denmark and India, and low precision countries are: Mexico, Japan, Philippines, Thailand, Indonesia, Malaysia, Korea, Argentina, Turkey, and Brazil. Standard errors clustered by year are in parentheses. ***, **, * denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.

TABLE A7: ANALYSIS OF CRISES USING LOGIT MODELS

Model:

$$D\_Crisis_{c,t} = \alpha + \sum_{i=1}^{2}\beta^{i} \times AccountingSignal^{i}_{c,t-n} + \lambda \times \text{Lag Crises Indicator}_{c,t} + \sum_{k=1}^{18}\gamma^{k} \times LeadingIndicators_{c,t-n} + \varepsilon_{c,t}$$

$I_{C_H} = 1$: if the country has high accounting precision, 0 otherwise.

$I_{C_L} = 1$: if the country has low accounting precision, 0 otherwise.

	(1)	(2)	(3)	(4)
	Prior period [-n =-1]		*Concurrent* [-n =0]	
	High accounting precision countries	Low accounting precision countries	High accounting precision countries	Low accounting precision countries
	coefficient (se)	coefficient (se)	coefficient (se)	coefficient (se)
$Accruals_{c,t}$ β^1	-1.357	-4.892**	-62.545**	9.246*
	(12.75)	(2.49)	(28.10)	(5.14)
$Profitability_{c,t}$ β^2	-28.959	4.134	-317.231***	2.891
	(28.64)	(2.86)	(81.70)	(6.39)
F- test: β^1, $\beta^2 = 0$ [*P-value*]:	χ^2 (2) = 1.09 [0.579]	**χ^2 (2) = 5.70 [0.058]**	**χ^2 (2) = 15.48 [<0.001]**	χ^2 (2) = 0377 [0.152]
Leading indicators from Table A2 and time trend	Included	Included	Included	Included
Indicator (crisis within last 3 yrs)	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes
SE clustering on year	Yes	Yes	Yes	Yes
# country-years	143	151	151	160
Pseudo R^2	0.389	0.379	0.784	0.652

Notes: $D\_Crisis_{c,t}$ is an indicator variable indicating a crisis year. See Table 1 for crisis years. Refer to Table 3 for a definition of the country sample with high and low accounting precision, and to Table A2 and Table 4 for definitions of the leading indicator variables and accounting signals. Standard errors clustered by year are in parentheses. ***, **,* denote significance at 1 percent, 5 percent, and 10 percent respectively, using a two-tailed test.